Analysing Risk Preferences and Time Preferences with respect to Smoking Status and Smoking Intensity

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ECO5066W – Masters Dissertation

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The financial assistance of the National Research Foundation (NRF) towards this research is hereby acknowledged. Opinions expressed and conclusions arrived at, are those of the author and are not necessarily to be attributed to the NRF.

February 2019

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Abstract

Smoking is a leading cause of death worldwide, and thus the behavioural components need to be understood to mitigate the damage caused by the practice. The relationship between smoking and factors such as risk preferences and time preferences has been the subject of a growing body of literature. This paper evaluates experimental data from smokers and non-smokers at the University of Cape Town collected in 2016 and 2017. Maximum likelihood estimation is used to estimate models of risk preferences and time preferences. The results highlight that smokers are less risk averse than non-smokers; that smokers discount more heavily than non-smokers; that greater smoking intensity is correlated with lower risk aversion; and that greater smoking intensity is not related to discounting behaviour. In some specifications the relationship between smoking intensity and risk aversion is parabolic, and as such moderate smokers are less risk averse than heavy smokers and light smokers. In conclusion, smokers tend to discount more heavily than non-smokers, and lower smoking intensity is associated with greater risk aversion than higher smoking intensity.

Acknowledgements

I would like to thank my supervisors, Dr André Hofmeyr and Professor Harold Kincaid. They provided excellent advice and encouragement. Dr Hofmeyr in particular was very patient, and spent much time providing clear and insightful help. I was first introduced to this topic during my work as a research assistant under Dr Hofmeyr, which was a great learning experience and helped to prepare me for this thesis. It was a pleasure to work alongside my fellow research assistants, Olivia Rusch and Rinelle Chetty. I am grateful to the NRF for the generous funding which greatly facilitated this thesis. Last but not least, I am thankful for my family who supported and encouraged me over the course of my thesis.

Section 1: Introduction

Tobacco is one of the most widely used addictive substances in the world and its use constitutes the greatest non-communicable risk factor for mortality globally. It causes the death of millions and the sickness of millions more. Over the years there has been significant medical study of the effects of tobacco smoking and governments have come to recognise it as a pressing public health concern. This has led governments to pursue public health interventions to curb tobacco use, and, while the medical consequences of tobacco use are well understood, the relationships between economic preferences (risk preferences and time preferences) and smoking variables (smoking status and smoking intensity) are less well understood.

Much of the existing research into why people smoke has been done by psychologists. However, there is an increasing body of economic literature regarding both theoretical models of addiction as well as experimental investigations into the correlates of addictive behaviours. Risk preferences and time preferences have been honed in upon as possible factors which may differ between people who use tobacco and people who do not.

There are many complexities involved in measuring risk and time preferences, some include: how do people value different amounts of money? Do people accurately conceive probabilities or do they subjectively weight probabilities? How do people calculate the present value of future amounts? There are additional complexities regarding the experimental aspect of the investigation, for instance: Is it necessary to pay subjects for their choices? What experimental methods should be used to best elicit preferences?

This thesis will investigate the link between tobacco use, risk preferences, and time preferences using methods from experimental economics and structural econometrics. Tobacco use will be analysed across two metrics: smokers vs. non-smokers, and across smoking intensity. The data will be analysed across a range of statistical specifications to ensure the results are robust to various theoretical and econometric assumptions.

The broad findings are that smokers and non-smokers differ with respect to time preferences but not risk preferences, with smokers discounting the future more than non-smokers. While among smokers: greater smoking intensity (number of cigarettes smoked per day) is associated with a difference in risk preferences but not time preferences, with greater smoking intensity being associated with less risk aversion.

Section 2 reviews the literature. Firstly, it contextualises tobacco use historically, in the world, and in South Africa, as well as considering the cost associated with smoking. It then relates tobacco use to economic theory by considering the nature of addiction and how addiction can be modelled in economic terms. Finally, it considers the literature on how smoking relates to risk and time preferences, comparing how these preferences vary across smoking status (smokers vs. non-smokers) as well as across smoking intensity (such as cigarettes smoked per day).

Section 3 describes the experimental design and displays the sample summary statistics. Section 4 describes the statistical methods used to analyse the data.

Section 5 presents the results. Firstly, the risk preferences of smokers and non-smokers are compared using expected utility models and rank dependant utility models. Secondly, the time preferences of smokers and non-smokers are compared using a range of discounting parameters and utility functions. Thirdly, the risk preferences of smokers are analysed in terms of smoking intensity, with a variety of utility functions and smoking intensity metrics being used. Finally, the time preferences of smokers are analysed in terms of smoking intensity, with a variety of utility functions, discounting parameters, and smoking intensity metrics being used.

Section 6 provides a discussion of the results, contextualising them within the existing literature and considering the differences between specifications – specifically different metrics of smoking intensity. Finally, Section 7 concludes.

Section 2: Literature Review

a. The Context

The practice of smoking tobacco dates back to 4000 BC in Mesoamerica. It was used for a variety of reasons, ranging from purported medicinal benefits and appetite suppression to religious ceremonies. Upon contact with Spaniards, tobacco smoking was adopted readily by the colonisers and later, the inhabitants of Europe itself, albeit primarily as a luxury commodity rather than for religious reasons or purported medicinal benefits (Haustein & Groneberg, 2009).

Tobacco consumption quickly became popular, and with its meteoric rise in popularity came various restrictions on its trade and condemnation of its use. In the early 1600s, England put a ban on Spanish tobacco in order to bolster the nascent English tobacco industry, and taxes and duties on tobacco proved to be lucrative sources of government income. Similarly, in 1742, Prussia banned tobacco smoking due to the associated risk of fire. The 1800s saw some of the first scientific inquiries into tobacco, which resulted in various anti-tobacco organisations (Haustein & Groneberg, 2009).

By the early 1900s, the consumption of tobacco was widespread in the Western world. Its consumption was bolstered by the inclusion of cigarettes in World War I and World War II rations, as well as marketing campaigns to convince women to smoke cigarettes – smoking had previously been an exclusively male practice (Haustein & Groneberg, 2009).

German scientists in the 1920s were the first to note the connection between smoking and lung cancer. Germany was the first state to embark on a comprehensive campaign against the smoking of tobacco: condemning its use, funding research on the subject, applying specific bans on its consumption, banning its advertisement, and putting into place taxes on its sale

(Young, 2005, p 252). However, after the war the Allied powers failed to appropriate the German scientific findings regarding tobacco (Proctor, 1996).

After World War II numerous scientific studies were published in the UK and the US which suggested a relationship between smoking and lung cancer. This inquiry caused the tobacco industry to pursue marketing campaigns which suggested that smoking was not dangerous (e.g., “More doctors smoke Camels than any other cigarette”). However, as the relationship between smoking and lung cancer became unequivocal and widely accepted, advertising strategies stopped claiming that smoking benefits one’s health (Gardner & Brandt, 2006). In 1964 a report on the relationship between smoking and health was published by the Surgeon General of the US. This report named smoking a health hazard, and is often credited as the turning point in US public opinion on smoking (Young, 2005).

This change in perception has led to a decrease in smoking prevalence globally, and specifically in the developed world. However, global statistics belie salient differences between countries: in a large proportion of less regulated and less informed developing countries smoking prevalence has increased and in some such countries is projected to increase further. The magnitude of this shift is such that smoking prevalence is now greater in developing countries than it is in developed countries; prevalence was greater in developed countries up until 1990 (Ng et al., 2014).

The World Health Organisation (WHO) (2009) found that tobacco use represents the highest non-communicable global risk factor for mortality – being responsible for 9% of deaths globally (while high blood pressure is responsible for 13%). This is equivalent to 6 million deaths per year and $500 billion in economic damages, and constitutes the leading cause of preventable death (World Health Organization, 2013). Smoking was found (in 2012) to be significantly more prevalent globally among males (31%) than it is among females (6%) (Ng et al., 2014).

Disability-adjusted life years (DALYs) is a way of measuring the impact of a disease or condition on people’s lives without directly referring to mortality. Globally in 2009, tobacco use ranks sixth for most DALYs lost at 3.7% of the total; however, in middle-income countries smoking ranks third, accounting for 5.4%. In comparison, alcohol is third globally (4.5%) and first in middle-income countries (7.6%) (World Health Organization, 2009).

Smoking prevalence in Africa is predicted to rise, while smoking prevalence in South Africa is predicted to fall (World Health Organization, 2015). The South African gender differences in smoking prevalence are similar to global rates – with 29% of males and 7% of females smoking. Smoking is most common among Coloured adults, followed by Indians, Whites, and black Africans (Reddy et al., 2015).

The South African government employs a range of strategies to dissuade people from smoking. The measures include a sin tax on the sale of tobacco products, a ban on the advertising and promotion of smoking products, restrictions on where smokers can smoke (e.g., smokers cannot smoke within restaurants, unless they are in a designated smoking area), and prohibiting people under the age of 18 from buying or selling tobacco products (Rose-Innes, 2017). The South African government is currently considering putting in place further measures to dissuade smoking, such as plain packaging and other further restrictions (Van Der Merwe, 2016).

b. Smoking and Economic Theory

Smoking presents an interesting economic quandary from a theoretical perspective: given that smokers often profess regret regarding their habit, why do they smoke? This problem generalises to all addictive behaviours. To investigate it this paper will briefly consider: what addiction is; whether addiction is best characterised by disease or choice models; and how different economic models seek to explain addiction.

The fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5, American Psychiatric Association, 2013, p 571) defines tobacco use disorder as:

> "A problematic pattern of tobacco use leading to clinically significant impairment or distress, as manifested by at least two of the following, occurring within a 12-month period:"

following which is a list of 11 diagnostic criteria.[1] The definition and criteria, while adapted to smoking in this case, are general and applicable to all substance-related and addictive disorders. A disorder is considered mild if the individual presents 2-3 criteria; moderate, 4-5 criteria; and severe, 6 or more criteria.

There have been a number of criticisms of the DSM, such as: the criteria used to judge addictive disorders are open to interpretation – "How harmful do the consequences have to be for them to count?"; "addiction" has changed from describing the behaviour to explaining the behaviour (Ross et al., 2012); and, it is possible to have 5 individuals with mild disorders (2 symptoms each) who do not share any overlapping symptoms.

[1] For example, "There is a persistent desire or unsuccessful efforts to cut down or control tobacco use."

While issues do exist regarding the definition of addiction in the DSM-5, it is nonetheless the most widely used diagnostic instrument for tobacco use disorder and the result of decades of refinement.

Addiction: choice or disease?

The DSM-5 describes what criteria to look for in order to diagnose addictive behaviour, but it does not describe the mechanisms which drive it. An example of why this is important is the question: is addiction a disease or the outcome of choices made by an economic agent? The answer to this question determines the degree to which addiction is a function of agency, and has implications regarding related behaviours and policy interventions.

Among the first scientific proponents of the disease model of addiction was the Journal of Inebriety, which was published in the late 19th and early 20th centuries (as described by Weiner and White (2007)). The journal explicitly stated that intemperance (alcohol addiction) is a disease which can be cured similarly to how other diseases are cured, and that it can be inherited or acquired.

This model was opposed by the public of the time, as it described the state of the inebriated not to be a function of their agency, but rather a function of exogenous factors. This was seen as excusing or even encouraging the excessive consumption of alcohol (Weiner & White, 2007).

Addiction is defined as a disease by various modern organisations, such as: the American Society of Addiction Medicine (2011); the National Institute on Alcohol Abuse and

Alcoholism (2017); and, the National Council on Alcoholism and Drug Dependence (2015). For example, the American Society of Addiction Medicine (2011) defines[2] addiction thus:

> "Addiction is a primary, chronic disease of brain reward, motivation, memory and related circuitry. Dysfunction in these circuits leads to characteristic biological, psychological, social and spiritual manifestations. This is reflected in an individual pathologically pursuing reward and/or relief by substance use and other behaviors.
>
> Addiction is characterized by inability to consistently abstain, impairment in behavioral control, craving, diminished recognition of significant problems with one's behaviors and interpersonal relationships, and a dysfunctional emotional response. Like other chronic diseases, addiction often involves cycles of relapse and remission. Without treatment or engagement in recovery activities, addiction is progressive and can result in disability or premature death."

All three definitions referenced above describe addiction as a chronic, often-relapsing brain disease characterised by the compulsive or pathological use of drugs.

Heyman (2009) challenges the disease model of addiction on matters relating to genetics and agency. Heyman points out that addicts choose to quit their drug habits for reasons such as wanting to be better parents, to avoid potential legal ramifications, and financial constraints. In addition, addicts respond to drug prices, and contingency management programmes have been effective at incentivising addicts to quit. These facts challenge the idea that addiction is compulsive behaviour and instead suggest that addiction is voluntary behaviour, which is moderated as a function of the costs and benefits which accrue to the individual. Heyman (2009) further notes that, while addiction has a genetic underpinning, genes do not

[2] The definition presented here is the short definition, as opposed to the long definition which is more technical; see https://www.asam.org/resources/definition-of-addiction for more details.

deterministically predict addiction and that social and environmental factors play a contributing role.

A synthesis of the disease and choice models of addiction is proposed by Ross et al. (2012): the models are not contradictory because they approach the problem at different levels of analysis. Heyman's choice model analyses addiction at the behavioural level, while the disease model understands addiction at the molecular level. According to this thesis, these two levels of analysis complement, rather than contradict, each other.

I investigate the potential behavioural correlates of tobacco smoking so this study is in the tradition of Heyman (2009). But, given the reconciliation provided by Ross et al. (2012), this is not inconsistent with a molecular account of addiction.

Economic models of addiction

This paper will now consider economic models of addiction, notwithstanding the fact that behavioural analyses do not fully explain the phenomenon of addiction.

The model of rational addiction, developed by Becker and Murphy (1988), is designed to explain addiction based on the rational choices of an economic agent. The agent maximises utility over time where utility depends on a stock of addictive capital, and consumption of addictive and non-addictive goods. Importantly, the marginal utility of the addictive good depends on the stock of addictive capital – as the stock of addictive capital increases the marginal utility of the addictive good increases (this simulates addiction). Agents have complete information of future events and discount exponentially, thereby ensuring that their choices are consistent across time.

This model allows for aspects of addiction, such as: tolerance (increased consumption of the addictive good increases the addictive stock and thus results in decreased future utility), withdrawal (deceased consumption of the addictive good leads to a short-term fall in utility), and the crowding out of non-addictive goods (increased consumption of the addictive good leads to a decrease in the marginal utility of the non-addictive good).

A criticism of this model is that while it captures consumption through time, it does not incorporate stochastic uncertainty (e.g., will a smoker get lung cancer or not). Another criticism is that the model implies that addicts choose to become addicted, but this disregards the possibility that some addicts regret their addiction, or that addiction is voluntary but unintentional.

Over time the literature grew to incorporate models which accounted from incomplete information and stochastic uncertainty. Orphanides and Zervos (1995) develop a model based on that of Becker and Murphy where addictive goods are not equally harmful to all, and where the degree to which the addictive good is addictive and harmful to an individual is unknown initially. Individuals update their beliefs regarding how they are affected by additive goods as they consume them. The consumption decisions are optimal in an expected utility maximising sense and dynamically consistent given the information available.

This model allows for behaviour such as "trying a drug once" and hoping that one does not suffer great harm nor become heavily addicted. It is more realistic than purely deterministic models, however, agents are still assumed to be rational and time consistent for their given knowledge.

The literature further expanded to incorporate time-inconsistent behaviour, which is behaviour characterised by preferences shifting over time.[3] Dual Self models, such as that of Fudenberg and Levine (2006), describe a model where an individual has two "selves" – one self is more short-run (SR) oriented and the other self is more long-run (LR) oriented. These

[3] For example, deciding in the morning that you will go for a run in the evening, but in the evening you do not go for a run.

selves "fight" for control over the individual – as the cost of self-control increases the preferences of the SR self supersede those of the LR self. This leads to the agents being able to make time-inconsistent choices.

In Fudenberg and Levine (2012), the original 2006 model is expanded upon by including a stock of willpower which affects how current choices affect future decisions. Other literature in this area includes Chatterjee and Krishna (2009), who describe a two period stochastic model in which the SR self takes control in the second period with some probability.

The Fudenberg and Levine (2012) model differs significantly from the earlier Becker and Murphy model. It is stochastic, incorporates risk preferences, and allows for time-inconsistent choices. It also accounts for features of addiction such as relapse after a quit attempt, and the regret many addicts feel with regard to their first use of drugs.

These theoretical economic models of addiction, while differing in form, suggest the importance of investigating the relationship between risk preferences, time preferences, and addiction. The variety and complexity of the models of addiction suggests the importance of careful experimental design and valid statistical practices to accommodate the underlying theory.

c. Smoking: Risk Preferences and Time Preferences

Many studies have investigated the link between risk preferences, time preferences, and smoking behaviour. Studies have used different metrics and practices, often updated by theoretical refinement and empirical findings. To investigate these matters, this paper will consider: smoking and risk preferences; smoking and time preferences; smoking intensity, and risk preferences and time preferences.

Smoking and Risk Preferences

An intuitive link between smoking and risk preferences is that a less risk averse agent may be willing to enjoy the benefits of smoking at the expense of the possibility of a serious illness (e.g., lung cancer). In this section I will review two older studies in this literature, discuss the key findings and pitfalls of the literature, and discuss the methods and findings of more recent studies.

Mitchell (1999) conducted a study on adults in the US and compared the choices of 20 smokers and 20 "never-smokers".[4] Subjects were asked to choose between: option one which paid $10 with various probabilities (ranging from 0.1 to 1) and $0 with the complementary probability; and, option 2 which paid out an amount with certainty, where these amounts varied from ($0.01-$10.50). The options were randomly ordered and the subjects were paid for one of the questions of this task, chosen at random.

Risk attitude was modelled using probability discounting, which is a method of analysing choices made under risk by interpreting the probability of a reward as a delay to the reward. Non-linear least squares regression (NLLS) was used to estimate point estimates of risk aversion, which refers to aversion to variability of outcomes.[5] Point estimates were used as data for analysis, and no relationship was found between smoking and risk aversion.

Reynolds et al. (2004) sampled 25 smokers and 29 never-smokers from the adult population of the US. Subjects were required to choose between $10 received with some associated probability (ranging over 0.25-1) and a smaller amount received with certainty. The smaller amount was increased if the $10 option had been chosen previously and the smaller amount

[4] Smokers were defined as people who smoked 15 or more cigarettes a day. "Never smokers" were defined as people who had never smoked a cigarette in their life.
[5] Likewise, risk neutrality indicates that an individual will be indifferent between rewards which have the same expected value (regardless of differences in probability), and risk-loving behaviours indicate that an individual is willing to accept a risky reward over a safer reward.

was reduced if the smaller amount had been chosen previously.[6] This method is known as titration. The risk preference choices were interspersed with time preference choices. Subjects were paid either for a choice on the risk preference task or the time preference task, drawn at random.

Risk preferences were modelled using probability discounting. NLLS was used to estimate point estimates of risk aversion, and point estimates were used as data for analysis. Smokers were found to be less risk averse than never-smokers, which accords with our basic intuition that smokers are less risk averse than never-smokers.

In addition to these studies, there are a large number of studies with various experimental designs and statistical methods. The aspects of design and methods which will be considered are: incentive size and nature, sample size and composition, elicitation, probability range, utility model, and statistical methods.

Hypothetical prizes are not incentive compatible – i.e., there are no costs for wrong answers so how do you know subjects are answering truthfully, and even an earnest subject may respond differently when there's money on the line. A real prize which is too small may also not be incentive compatible, and relative rates of income for the time taken to complete the task should be taken into account. Hypothetical prizes (such as Ohmura et al. (2005) and Ida (2014)) and real prizes (such as Mitchell (1999), Reynolds et al. (2004), and Harrison et al. (2010)) are both fairly common in the literature but we should clearly lend more credence to studies employing real rewards.

Sample size is important, as an insufficient sample size may not yield the statistical power necessary to draw valid statistical inferences. Hypothetical prizes reduce costs per subject

[6] For example, you choose between $10 with probability 0.75 and $5 with certainty. You choose $10.
You now choose between $10 with probability 0.75 and $7.50 with certainty. You choose $7.50.
You now choose between $10 with probability 0.75 and $6.25 with certainty, et cetera.

which allows for a larger sample, but hypothetical prizes have their own costs, as mentioned above. Sample composition is another area where financial constraints limit what is ideal. Ideally the sample would be representative of the population in which you are working; however, this is expensive, and, while student samples may cost less, student samples may hinder the external validity of the study.

Sample size varies significantly in the literature, from small samples with 0-100 subjects (such as Mitchell (1999) with 40 subjects and Reynolds et al. (2004) with 54 subjects), to medium samples with 101-300 subjects (such as Harrison et al. (2010) with 252 subjects and Harrison et al (2018) with 175 subjects), to large samples with over 300 subjects (such as Ida and Goto (2009) with 12530 subjects and Ida (2014) with 494 subjects). Both large samples here had hypothetical prizes.

The titration elicitation method is often used in this literature but it is vulnerable to being "gamed" if subjects realise the structure of the method. If the subject chooses the higher amount, the lower amount increases in the next round, and so it might make sense for a subject to misrepresent his preferences for a chance at a larger prize. This problem is partially mitigated by random ordering. Another problem with titration is that it punishes mistakes made by the subject, which would lead to the mis-estimation of the subject's preferences.[7]

As research in this field has progressed, the titration elicitation method has become less popular. In the early 2000s it was used in a variety of studies such as Reynolds et al. (2004) and Ohmura et al. (2005). More recently, the choice elicitation method has become more

[7]For example, you choose between $10 with 0.75 probability and $5 with certainty. You choose $10.
But suppose this is a mistake. You meant to choose $5. Your indifference point has a value less than $5.
You now choose between $10 with 0.75 probability and $7.50 with certainty. You choose $7.50. etc.
Due to the narrowing range of choices you will never be able to choose a value less than $5. Thus you are punished for an earlier mistake and can't reach your indifference point (and thus are always choosing riskier options than you would like to choose).

popular. In this method the subject makes a choice between two lotteries. The values of the lotteries are not dependant on the previous choices of the subject, and thus do not have the pitfalls regarding mistakes and "gaming" present in titration. The choice elicitation method was used in studies such as Ida and Goto (2009) and Harrison et al. (2018).

A small number of probabilities used in the lotteries may constrain the ability of a statistical model to determine the accurate estimates of preferences or utility. For example, Reynolds et al. (2004) used 5 probabilities ranging over [0.25,1], whereas Harrison et al. (2010) used 10 probabilities evenly spaced over [0.1,1].

A common mistake in the literature is that after point estimates for risk preference are estimated, these point estimates are subsequently used as data in further statistical analysis. This is not statistically valid as it disregards the uncertainty inherent in the original point estimates. A more statistically valid approach is to use a method which incorporates the uncertainty of the original point estimates in the subsequent statistical analysis, such as that adopted by Harrison et al. (2010) and Harrison et al. (2018).

An example of a methodologically sound study is Harrison et al. (2018) which sampled 108 smokers and 67 non-smokers from the student population of the University of Cape Town, South Africa. Subjects made 40 choices in a choice method risk preference task, one of which was selected at random at the end of the experiment and paid out. The data were analysed using a constant relative risk aversion (CRRA)[8] utility function over outcomes and various models of choice under risk, including Expected Utility (EU) Theory[9] and Rank Dependent Utility (RDU) Theory.[10] Maximum likelihood estimation was used to estimate risk preferences as a linear function of demographic characteristics and task parameters. The use

[8] As defined in Statistical Methods, equation (1).
[9] As defined in Statistical Methods, equation (2).
[10] As defined in Statistical Methods, equation (8).

of maximum likelihood estimation avoids the problem of using point estimates (of the risk preferences of individuals) as data. The study found that there were no statistically significant differences in the risk preference of smokers and non-smokers.

Differences in designs and methods make the comparison of studies somewhat difficult – for example, how much does one weigh a study with hypothetical rewards versus one with real rewards? How much does one weigh a study that has a small sample versus one which has a medium or large sample? However, a detailed review conducted by Harrison et al. (2018) shows that the relationship between risk preferences and smoking status is equivocal.

Smoking and Time Preferences

An intuitive link between smoking and time preferences is that a more present orientated agent may be willing to enjoy the benefits of smoking – which accrue in the short run – at the expense of the long run costs, which the agent discounts more than average. In this section, I will review two older studies, discuss the key findings and pitfalls of the literature, and discuss the methods and findings of more recent studies.

In Mitchell (1999) the subjects were required to choose between "smaller sooner" (SS) amounts and "larger later" (LL) amounts of money. The LL was always $10, while the delay to the LL varied between 0 and 365 days. The amount of the SS varied between $0.01 and $10.50, and the SS had no delay in payment (i.e., it was received immediately). The time preference choices were randomly ordered and the subjects were paid for one of the questions of this task, chosen at random.

The subjects were assumed to engage in hyperbolic discounting, as opposed to, for example, exponential discounting. The type of discounting will impact the degree to which costs or benefits are discounted, with hyperbolic discounting leading to greater short term discounting than exponential discounting and the potential for time inconsistency.

The possibility of non-linear utility was not considered.[11] Non-linear least squares regression (NLLS) was used to estimate point estimates of the hyperbolic discounting parameters, and point estimates were used as data for analysis. Mitchell found that smokers discounted more heavily than never-smokers.

The subjects in Reynolds et al. (2004) had to choose between a constant LL of $10 with some delay ranging over 1-365 days and an SS with no delay which varied in amount. The SS was increased in the following round if the LL was chosen and decreased in the following round if the SS was chosen. As with the risk preference task, titration was used in order to find the indifference point by narrowing the range of possible values it could take. The order was random and risk preference choices were intermixed with time preference choices. Subjects were paid either for one of the choices from the time preferences task or the risk preference task, drawn at random.

Like Mitchell, hyperbolic discounting was assumed and their model did not allow non-linear utility. NLLS was used to estimate point estimates of the hyperbolic discounting parameter, and point estimates were used as data for analysis. It was found that smokers discounted more heavily than never-smokers.

There are a large number of studies with various experimental designs and statistical methods, and (while we covered many of these differences in the risk preference section) a number of these differences are specific to time preferences. The aspects of design and

[11] Linear utility describes the idea that utility increases linearly with e.g., money. By way of example: if you double your money and your utility doubles then if you triple your money your utility will triple. Non-linear utility is the idea that an increase in money may result in a non-linear change to utility. This is important because if a subject has non-linear utility then his choices in a time preference task are a function of both his time preferences and his non-linear utility, and one must determine the relative strength of the parameters.

methods which will be considered are: time horizons, front end delays, utility functions, and discounting methods.

Very long time horizons (beyond a year) have the problem of almost always using hypothetical rewards (such as Ohmura et al. (2005)), which, as mentioned above, leads to questionable results due to the tasks not being incentive compatible. Furthermore, long time horizons with real prizes (such as Harrison et al. (2010)) may suffer from the problem of subjects doubting if the prize will be paid out, despite the best efforts of the researchers to alleviate such doubts.

Front end delays (FEDs) is an experimental design where the SS amounts are not paid out immediately, but instead after some delay (such as a day or a week). This is done to account for factors such as transaction costs, fears that the future payment will not be paid, and a present-bias or "passion for the present" any of which may cause mis-estimation of time preferences (Coller & Williams, 1999).[12] Specifically, the zero day FED allows for the estimation of "present-bias", while the seven day FED allows for estimation of long-term discounting.

Most studies in the literature assume that utility is linear over monetary prizes. This is not necessarily the case, as shown by Andersen et al. (2008). If the utility of a subject is non-linear over money then this causes the estimate of the discounting parameter to be biased. A utility function over monetary prizes can be estimated jointly with the parameters of a time preference model and used to improve the accuracy of predictions of time preferences.

[12] By way of example: A subject might choose the SS amount over the LL amount not due to him preferring the SS amount on the basis of his time preference, but preferring the SS amount on the basis that he fears that the future payment will not occur and so he would rather take the immediate payment.

The choices of the subjects are often modelled using hyperbolic discounting by assumption in the literature. However, the choices of the subjects could be modelled using other discounting functions, such as exponential or quasi-hyperbolic.[13]

Harrison et al. (2018) – the methodologically sound study from the previous section – approached time preferences by using risk preference data to estimate a utility function jointly with the parameters of a variety of discounting functions. Three FEDs were used (immediate payment, 7 days, and 14 days), and the longest LL delay was 98 days. Harrison et al. (2018) found that smokers had higher discount rates than non-smokers under every discounting specification.

Similarly to risk preferences, the comparison of studies investigating time preferences is made difficult by the heterogeneity of the characteristics of the studies. However, the literature, as reviewed in Harrison et al. (2018), appears to suggest that smokers discount the future at higher rates than non-smokers.

Smoking intensity

An intuitive link between risk preferences, time preferences, and smoking intensity is that perhaps heavier smokers are more risk-loving and discount more heavily than lighter or more moderate smokers. Put simply, perhaps not only whether a person smokes but also the degree to which a person smokes is correlated with risk and/or time preferences. The literature on smoking intensity is somewhat sparser than that of the smoker versus non-smoker literature. A common metric of smoking intensity is the Fagerström Test for Nicotine Dependence (FTND) (Heatherton et al., 1991), which scores smokers on a scale from 0 to 10.[14]

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[13] A quasi-hyperbolic function allows for time inconsistency, unlike an exponential function. The functional forms will be expounded upon in more detail in the Statistical Methods section.

[14] 1-2 indicates low dependence; 3-4, low-to-moderate; 5-7 moderate; 8-10, high.

In a study of Japanese adults, Ida and Goto (2009) found that heavy smokers tended to be less risk averse and discounted more heavily than light or moderate smokers, however the difference was not statistically significant. Smoking intensity was measured using FTND. The sample size was large (12530 total), and hypothetical rewards were used. A similar study by Ida (2014) found a statistically significant tendency for heavy smokers to discount more than light or moderate smokers, and for heavy smokers to be less risk averse. The sample was also large (494 total).

In a study of US adults, Reynolds et al. (2004) found that heavier smoking was statistically significantly correlated with greater discounting, but was not statistically significantly correlated with risk aversion. Smoking intensity was measured biomedically using carbon monoxide (CO) testing. The sample size was small (54 total) and subjects were compensated based on their choices.

In a study of Japanese adults, Ohmura et al. (2005) found that heavier smoking was statistically significantly correlated with greater discounting (in monetary gains but not monetary losses). Heavier smoking was not statistically significantly correlated with risk aversion. Smoking intensity was measured using cigarettes smoked per day, as well as estimated nicotine intake per day. The sample size was small (50 total) and the prizes were hypothetical.

In a study of South African students, Harrison et al. (2018) found that the number of cigarettes smoked had a (positive) parabolic relationship with discounting, with light smokers discounting the least, medium to heavy smokers discounting the most, and very heavy smokers discounting slightly less than medium smokers. Smoking intensity was measured using cigarettes smoked per day. The sample size was large (175 total) given that the prizes were not hypothetical.

There are fewer studies which investigate the link between risk preferences, time preferences, and smoking intensity than there are studies which compare smokers and non-smokers on those metrics. Nevertheless, the literature suggests that heavier smokers discount more than lighter smokers, and that there is no significant difference between heavier smokers and lighter smokers with regard to risk preferences.

I investigate whether these results hold in a sample of university students using an incentive compatible experimental design and a structural econometric approach to data analysis.

Section 3: Experimental Design and Summary Statistics

The data used in this thesis were collected from two sets of experiments conducted at UCT. The first set of experiments was part of a study analysing intertemporal risk preferences and subjective beliefs regarding smoking, while the second set of experiments was a part of a smoking cessation programme study.[15] The first set of experiments was run between November 2016 and March 2017, and the second set of experiments was run in August 2017. In all two sets of experiments, university students were contacted via email with an advert for the respective studies[16], which included a link to an online sign-up survey and mentioned the range of earnings a subject could expect.[17] A large number of people signed up for the first study and participants were randomly selected. A small number of people signed up for the second study and all valid[18] participants were selected.

Subjects who were selected to take part in the experiments were added to a website which allowed for communication and organisation regarding their experimental sessions. Subjects then chose a suitable time for their experimental session. Prior to the experimental session subjects were reminded twice[19] via text message of their upcoming session. The experimental sessions were conducted in a computer lab at UCT. For most subjects the computer lab would not have been more than a 10-minute walk away.

The computer lab was set up with cardboard dividers between the computers so that subjects would not look at or be distracted by other nearby subjects. On the computers software was

[15] The format of the cessation study was: screening, baseline, quit period, weekly follow-ups for a month, 3 and 6 month follow-ups. The data used in this thesis were taken from the baseline experiments.
[16] The adverts for the first study sought smokers and non-smokers to take part in a behavioural experiment, while the advert for the second study sought smokers who wished to quit smoking.
[17] For the first study: R400-R1500 ($67-$250 at PPP). For the second study: R800-R2000 (over the entire cessation study; $133-$333 at PPP).
[18] Participants in the second study were biochemically tested to prove that they were smokers and thus eligible for the programme.
[19] The night before, and the morning of, the session.

opened which would capture the experimental choices made by the subjects; additionally, an internet browser based questionnaire and an explanatory video were also opened.

Subjects were asked to arrive at the computer lab 15 minutes early and, once there, to wait quietly while a research assistant checked their name against a list. The sessions were run by one researcher and a minimum of two research assistants. The number of experimental sessions and size of the experimental sessions varied: for the eight sessions between November 2016 and March 2017 the median[20] size was 18; and, for the seven August 2017 sessions the median size was 12.

Upon entry into the computer lab subjects were asked to remain silent and find a seat at a computer. There was then a short introduction and students were asked to fill in an informed consent form. Following this there was a presentation explaining the broad structure of the experiments, that the payment for each section would be calculated at the end of each task and communicated to the subject, and how this payment would be calculated. If subjects had a question, they were invited to raise their hand and wait for a research assistant to answer it quietly in private.

After the completion of the introduction, subjects were instructed to read some written material[21] explaining the first task, and then subsequently watch a video with examples re-iterating the explanation. In the smoking cessation study (but not the earlier study) the first task would be either the risk preference task or the time preference task. Following its completion subjects had their payment for the first task calculated in front of them using dice to randomly select one of their choices. Subjects then read and watched a video for the second task.[22] In the first experiment there were two additional tasks following the initial

[20] The mean sizes of the experimental sessions were 18 and 13, respectively.
[21] With diagrams; which can be seen in appendix A.
[22] The time preference task if the risk preference task was done first, and vice versa.

two: an intertemporal risk preference task and a subjective beliefs task.[23] After the experimental tasks were finished, subjects completed a questionnaire on the computer. At this point, in the second set of experiments subjects were taken to do biochemical tests. All the sessions concluded with the subject being paid. Subjects received R50 for participation and any experiment earnings which accrued on the day of the experiment, while future payments were made via electronic transfer into the student's bank account.[24] The sessions lasted roughly 2 hours, and the average earnings were R919 and R604 for the first and second sets of experiments, respectively.[25]

Risk Preference Task

The risk preference task required subjects to choose between two lotteries on each screen presented to the subject on the computer. The details of these lotteries were conveyed visually through pie charts, with textual descriptions accompanying below. An example of the task can be seen in Figure 1 below. Subjects made 90 choices over randomly ordered lottery pairs, after which one was randomly selected, and the earnings were calculated.

The prizes ranged from R0 – R700 ($0 - $117 PPP), while the associated probabilities ranged from 0.1 to 1. Some prizes were "double or nothing" – if the subject chose the lottery and it was randomly selected for payment, then the associated prize either would be doubled or the subject would receive nothing (each option with a 0.5 probability).

[23] This thesis will not analyse the data from the intertemporal risk preference task or the subjective beliefs task.
[24] Students without bank accounts were not eligible for the experiments. This did not appear to hinder sign ups.
[25] The first experiment had four tasks, which is why there is a R300 difference. Comparing like with like, the average earnings of the first experiment was R573.

Figure 1

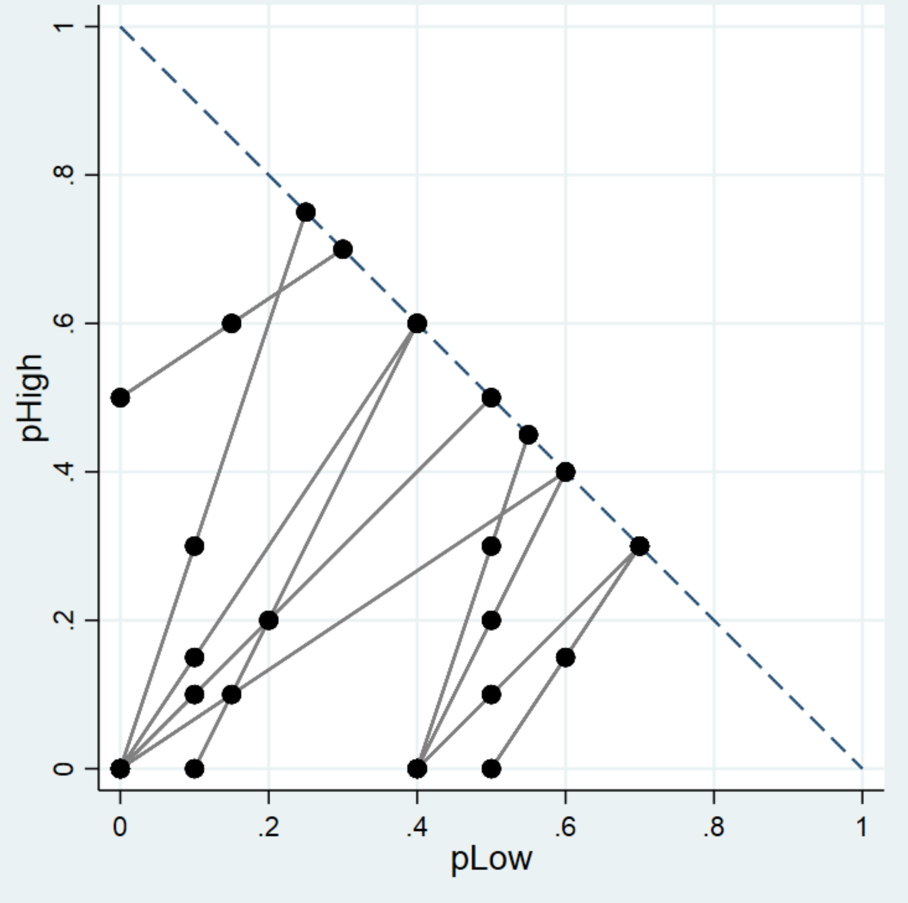
The 90 risk preference lottery pairs were chosen to investigate a broad range of risk preferences, while accounting for the possibility that both utility functions and probability weighting functions could affect choice under risk. The lotteries pairs were derived from four sources: 24 from Wakker, Erev, and Weber (1994); 30 from Harrison, Martinez-Correa, and Swarthout (2015); 6 from Cox and Sadiraj (2008); and, 30 from Loomes and Sugden (1998).

The Wakker, Erev, and Weber lotteries were designed to test the comonotonic independence axiom of RDU. The Cox and Sadiraj lotteries were designed to test whether subjects reacted differently when presented a "safe" vs a "risky"[26] lottery across a range of expected values –

[26] In a "safe" lottery the subject receives an amount with certainty, while in the "risky" the subject is presented with a lottery, the expected value of which is slightly higher than that of the safe lottery. The safe lottery has a

the idea here being that subjects may behave differently (in a more risk averse manner) when the lotteries have high expected values compared to when they have low expected values. The Harrison, Martinez-Correa, and Swarthout lotteries were designed to test the ability of subjects to reduce compound lotteries to simple lotteries. This was achieved by presenting subjects with a “double or nothing” type lottery pair, as well as an actuarially equivalent simple lottery pair. Finally, the Loomes and Sugden (LS) lotteries were designed to test EU by considering choice patterns within a Marschak-Machina (MM) triangle with variation in the gradient of EU-based indifference curves. The prizes were the same across the LS lottery pairs (R60; R180; R300).

Figure 2: Marschak-Machina triangle of selected lotteries



wide variety of values from R60 to R540, while the risky lottery is consistently a 50-50 lottery with options of R30 (or R60) below and R40 (or R70) above that of the safe lottery.

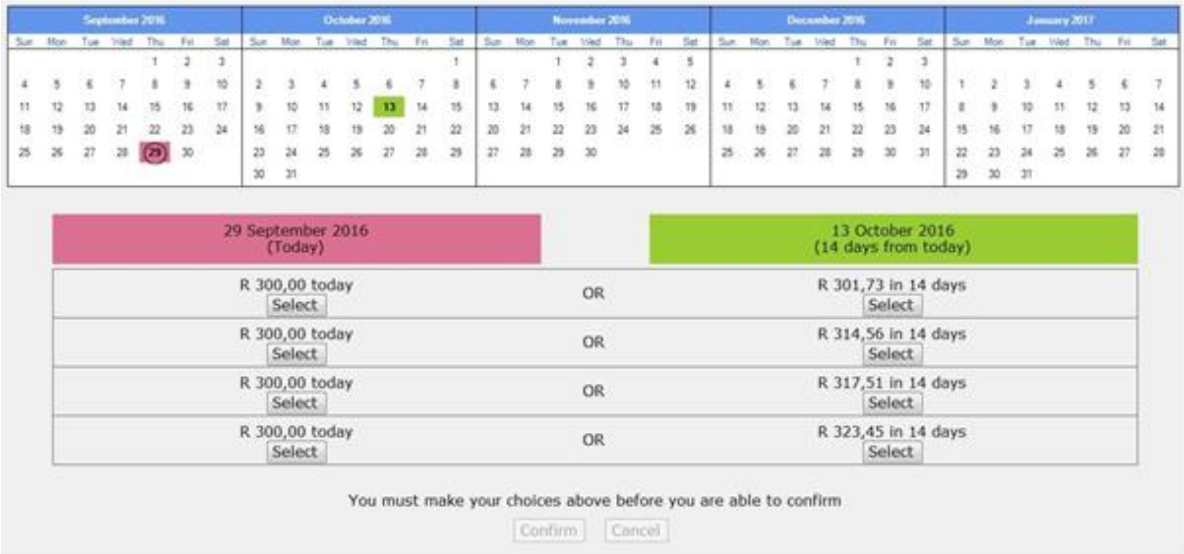
The LS lotteries are represented above in Figure 2 in a MM triangle. Each point on the Marschak-Machina triangle represents a lottery, while two (or more) points connected by a line represents a lottery pair (or a set of lottery pairs). The vertical axis represents the probability of the highest prize in the lottery (R300), the horizontal axis represents the lowest prize of the lottery (R60), and, the middle prize (R180) is represented by the complement of the sum of the probabilities of the other two prizes.[27] The gradients of the lines connecting the lotteries represent risk preferences associated with the lottery pairs: a steeper gradient is associated with risk averse; a 45° gradient, risk neutral; a shallower gradient, risk-loving.[28] Figure 2 shows that the risk preference task provides good coverage of the MM triangle.

Time Preference Task

The time preference task required subjects to make 4 choices per screen. Subjects would choose between SS amounts and LL amounts. The SS amounts remained fixed over the 4 choices, while the LL amounts increased over the 4 choices. A calendar was displayed and the payment dates were highlighted, with textual descriptions accompanying below. An example of the task can be seen in Figure 3. Subjects made 60 choices, after which 1 was randomly selected, and the earnings were calculated.

[27] Visually: the R180 prize has a probability of 1 at the origin of the graph, and has a probability of 0 at any point along the dotted line.
[28] In the case of a gradient greater than 1: the expected value of the "safer" lottery would be greater than the expected value of the "risky" lottery. A gradient equal to 1 has lotteries of equal EVs. Finally, a gradient of less than 1 has a "safer" lottery with an EV less than that of the "risky" lottery.

Figure 2



Two Front end delays (FEDs) were used for the SS prizes: zero days and seven days. Other design elements included: two principles (R250 and R400); four LL time horizons (7, 14, 42, and 84 days); and 14 nominal annual interest (rates ranging from 5% to 200%). From these parameters a battery of 112 choice pairs were created, of which 60 were randomly selected without replacement for the subject to complete.

Descriptive Statistics

Descriptive statistics of the sample are displayed in Table 1. The total number of subjects is 235. Males make up 62% of the sample; the mean age is 22 years old[29]; 37% of the sample is Black, 21%, Coloured[30], 16%, Indian, and, 22%, White.[31] Smokers comprise roughly 50% of the November to March sample[32], and 100% of the cessation sample; smokers comprise 71% of the total sample. Smokers in the total sample consumed an average of 8.90 cigarettes per

[29] The minimum age was 18. The standard deviation is 2.60.
[30] "Coloured" is an official term used in South Africa to refer to people of mixed race, especially people of Cape Malay origins.
[31] The remaining 4% is categorised as "other" or "prefer not to answer."
[32] Subjects were considered current smokers if they answered "Yes" to the question "In your entire life, have you ever smoked at least 100 cigarettes?" and they had smoked in the last 2 days.

day, with a corresponding standard deviation of 5.29. The Fagerström Test for Nicotine Dependence (FTND) (Heatherton et al., 1991) is a common test used to measure smoking intensity. The mean FTND for the total sample of smokers was 3.12[33], with a standard deviation of 2.05.

TABLE I: DESCRIPTIVE STATISTICS

	Experiment 1		**Experiment 2**		**Total**	
	Number	% or SD	Number	% or SD	Number	% or SD
Black / African	63	43%	23	26%	86	37%
Coloured	25	17%	25	28%	50	21%
Indian	19	13%	18	20%	37	16%
White	32	22%	20	22%	52	22%
Male	76	52%	70	78%	146	62%
Smokers	77	53%	89	99%	166	71%
Age (Mean SD)	21.48	2.37	21.62	2.94	21.53	2.60
Cigarettes (Mean SD)	8.42	5.89	9.58	4.84	8.90	5.29
FTND (Mean SD)	2.81	2.00	3.49	1.98	3.12	2.05
Sessions	8		7		15	
Median session size	18		13		17	
Observations	145		90		235	

[33] A score of 3-4 is consistent with low to moderate nicotine dependence.

Section 4: Statistical methods

The statistical methods used closely follow Andersen et al. (2008). Time preferences and risk preferences are jointly estimated using maximum likelihood estimation. The associated log likelihood function can be adjusted to accommodate different utility functions, models of choice under risk, and discounting models. A major benefit of this method is that the risk preference task can be used to estimate the utility function parameters, which allows the time preference task to focus on estimating the discounting parameters. This section will first consider the estimation of risk preferences, then time preferences, and finally joint estimation.

Risk Preferences

Let the utility of income be expressed by a power utility function exhibiting constant relative risk aversion (CRRA):

$$U(y) = y^r, \tag{1}$$

such that y represents a monetary prize in a lottery in the risk preference task, and r is the risk preference parameter to be estimated. For the cases: $r = 0$, $U(y) = \ln y$; and $r < 0$, $U(y) = -y^r$ (following Wakker (2008)). Under EU Theory the utility function determines risk preferences, and thus in this parameterisation: $r < 1$ [$r = 1$] [$r > 1$] results in a concave [linear] [convex] utility function and risk averse [neutral] [loving] behaviour.

For a given risk preference lottery i, let there be 3 outcomes[34] (such as in, e.g., Figure 1). Let $p(y_j)$ be the probability of outcome y_j occurring under that lottery, then the EU of lottery i can be expressed as:

$$EU_i = \sum_{j=1,2,3} [p(y_j) \times U(y_j)] \qquad (2)$$

The expected utility of a lottery is represented above as the sum of the utility of each outcome weighted by its probability. The expected utilities can be calculated for each lottery pair (with EU_R indicating the right-hand lottery, and EU_L, the left-hand lottery), given an estimate of r, and thus an index formed:

$$\nabla EU = EU_R - EU_L \qquad (3)$$

A cumulative normal distribution function can be applied to this index in order to transform it into a probit function $\Phi(\nabla EU)$, the domain of which is the possible values of ∇EU $(-\infty,\infty)$ and the range of which is the probability of lottery R being chosen [0,1]:

$$P(\text{Choose lottery R}) = \Phi(\nabla EU) \qquad (4)$$

In (3) when lotteries R and L have the same expected utility (i.e., $EU_R = EU_L$), then $\nabla EU=0$, which in (4) results in $\Phi(\nabla EU) = \Phi(0) = 0.5$ indicating that the likelihood of picking lottery R is equal to that of lottery L. Alternatively, if lottery R has greater [lesser] expected utility

[34] If the number of outcomes displayed is less than 3, then the probability of any non-displayed outcome is assumed to be zero.

than lottery L, then $\nabla EU>0$ [$\nabla EU<0$], which results in $\Phi(\nabla EU) > 0.5$ [$\Phi(\nabla EU) < 0.5$] indicating that it is more [less] likely that lottery R will be chosen over lottery L.

Assuming the CRRA utility function and the EU model are true, the likelihood of the risk preference responses depend upon the estimated value of *r*. Thus, for the risk preference task the following conditional log likelihood function can be formed:

$$\ln L_i^{RP}(r; z, X) = \sum_i[(\ln \Phi(\nabla EU) \times I(z_i = 1)) + (\ln \Phi(1 - \nabla EU) \times I(z_i = 0))], \quad (5)$$

where the z parameter represents the indicator function I(.) with $z_i = 1$ [$z_i = 0$] indicating a choice of lottery R [L], and the X parameter denotes a vector of individual characteristics of the subject (gender, population group, income etc.).

The structural maximum likelihood estimation approach allows for the easy estimation of dependent variables, specifically in this case the risk preference parameter *r*, as linear expressions of independent variables, specifically in this case the vector of individual characteristics X. This may be represented by the expression: $r = r_\alpha + r_\beta \times X$, such that r_α is a fixed intercept and r_β is the vector of coefficients associated with the vector X (of individual characteristics). Estimates of *r* have corresponding standard errors, which reflect the uncertainty of the point estimate. A point estimate and an associated standard error provide more informative data than simply a point estimate by itself.[35]

Additionally, the model allows for stochastic errors to be incorporated into the mechanism by which subjects choose between lotteries R and L (e.g., if the subject slightly prefers lottery R then the subject might make a mistake and pick lottery L instead). Wilcox (2011) provides the construct of "contextual utility" (CU) which modifies EU by allowing for stochastic

[35] The standard error allows the calculation of the statistical significance of the point estimate, from which it can be determined whether the point estimate differs from zero.

choice. This normalises the ∇EU index by restricting the range to [0, 1] and incorporates a behavioural error term. The augmented version of the ∇EU index of (3) can be seen below:

$$\nabla EU = [(EU_R - EU_L) / \lambda\ ] / \mu, \tag{6}$$

such that λ represents the normalising term and μ represents the behavioural error term. Specification (3) can be achieved by setting $\mu = 1$. As $\mu \rightarrow 0$ the choice between the lotteries tends towards an outcome solely determined by non-stochastic EU, while as $\mu \rightarrow \infty$ the choice between the lotteries tends towards an outcome solely determined by chance. The log likelihood can be updated so that r as well as μ can be estimated:

$$\ln L_i^{RP}(r, \mu; z, X) = \sum_i[(\ln \Phi(\nabla EU) \times I(z_i = 1)) + (\ln \Phi(1 - \nabla EU) \times I(z_i = 0))] \tag{7}$$

EU is not the only model of choice under risk – another commonly used model is the RDU model of Quiggin (1982). RDU differs from EU in that it assumes that subjects rank the outcomes of a lottery from worst to best, and then potentially distort the probabilities of the outcomes by attaching weights based on the rank of the outcome. The EU specification (2) can be adjusted to an RDU specification as follows:

$$RDU_i = \sum_{j=1,\ldots,n} [w(y_i) \times U(y_i)], \tag{8}$$

such that

$$w_j = \pi(p_j + \ldots + p_n) - \pi(p_{j+1} + \ldots + p_n), \tag{9}$$

for j = 1, … , n-1; and

$$w_j = \pi(p_j), \tag{10}$$

for j = n; with outcomes ranked from worst to best; and, such that

$$\pi(p) = p^{\gamma} / [p^{\gamma} + (1 – p)^{\gamma}]^{1/\gamma}, \tag{11}$$

for $0 < p < 1$. Expression (11) is a probability weighting function (PWF), which takes objective probabilities and transforms them into subjective weights, thus allowing for subjective distortions of probabilities. This specific PWF is popularly used and follows from Tversky and Kahneman (1992).

The estimation of a RDU model, with RDU as defined above, requires little alteration to the EU model specified previously. A PWF would replace the raw probabilities, and the log likelihood would estimate the parameter associated with the PWF, γ, in addition to r and μ. Alternative PWFs can be used (which would in turn require different parameters to be estimated).

Time Preferences

Let the utility of income be represented by some function U(·). The utility of income received at time *t* can be equated with the utility of income received at time $t + \tau$ through the use of discount factor, D:

$$U(y_t) = D \times U(y_{t+\tau}), \tag{12}$$

where $0 < D < 1$. There are different discount factors which can be used. A commonly used discount factor is the exponential discount factor:

$$D^E(t) = 1 / (1 + \delta)^t, \tag{13}$$

such that $t \geq 0$; and, with a discount rate of δ. This model has distinct features in that the discount rate δ is constant over time, and that the geometric series $\sum_{t\rightarrow\infty} D^E(t)$ converges. When considering time preferences we measure a subject's preferences between SS and LL ammounts. The SS prize can have a delay, thus (12) becomes:

$$[1 / (1 + \delta)^t]U(y_t) = [1 / (1 + \delta)^{t+\tau}]U(y_{t+\tau}), \tag{14}$$

such that the SS prize is received at *t*, and the LL prize is received at $t + \tau$. In the risk preference specification we use a measure of utility – described in (1). Power utility can be substituted into (14) to yield:

$$[1 / (1 + \delta)^{t}](y_t)^{r} = [1 / (1 + \delta)^{t+\tau}](y_{t+\tau})^{r}, \qquad (15)$$

For expressions (14)-(15), the left hand side represents the present value (PV) of the utility of money of the SS amount, while the right hand side represents the PV of the utility of the LL amount. Thus we can create the PV formulae:

$$PV_{SS} = [1 / (1 + \delta)^{t}](y_t)^{r}, \qquad (16)$$

and,

$$PV_{LL} = [1 / (1 + \delta)^{t+\tau}](y_{t+\tau})^{r} \qquad (17)$$

Similarly to the risk preferences section, an index can be formed which describes which prize will be preferred for a given δ and *r*:

$$\nabla PV = (PV_{SS} - PV_{LL}) / \nu, \qquad (18)$$

where ν is a behavioural error term, similar in form to the behavioural error term of the risk preference task, μ. This index can then be transformed using a cumulative normal distribution function, which yields:

$$P(\text{Choose SS reward}) = \Phi(\nabla PV) \qquad (19)$$

If $PV_{SS} = PV_{LL}$ then $\nabla PV = 0$, and $\Phi(\nabla PV) = 0.5$, which indicates indifference between the SS and LL prizes. Alternatively, when $\Phi(\nabla PV) > 0.5$ [< 0.5] the SS [LL] prize will be more likely to be chosen.

Assuming the CRRA utility function, the EU model, and the exponential discounting model are true, the likelihood of the time preference responses depend on *r*, δ, μ, and ν. Thus, for the time preference responses the following log likelihood function can be created:

$$\ln L_i^{TP}(r, \delta, \mu, \nu; z, X) = \textstyle\sum_i[(\ln \Phi(\nabla PV) \times I(z_i = 1)) + (\ln \Phi(1 - \nabla PV) \times I(z_i = 0))] \qquad (20)$$

The responses to the risk and time preference tasks can be estimated jointly using a log likelihood function maximising over the risk (7) and time (20) expressions:

$$\ln L_i(r, \delta, \mu, \nu; z, X) = \ln L_i^{RP} + \ln L_i^{TP} \qquad (21)$$

The joint model allows the estimation of risk preferences and time preferences. The joint estimation of risk preferences and time preferences allows for the estimation of risk preferences to construct a utility function which can be used in the estimation of time preferences. This is not possible when risk preferences and time preferences are estimated separately, and thus separate estimation leads to a loss in accuracy relative to joint estimation. Specifically, with regard to the possibility of the non-linear utility of money flows, the possible existence of which would confound the estimation of time preferences, as explained by Andersen et al. (2008).

Section 5: Results

The data are analysed using a broad array of statistical specifications and metrics. This section will begin by presenting the risk preference results comparing smokers with non-smokers. It will continue by presenting the time preference results comparing smokers with non-smokers. Lastly, this section will present risk preference and time preference results focussing on smoking intensity.

a. Risk Preferences: Smokers vs. Non-Smokers

Risk preferences are analysed using EU Theory and RDU theory. Each of these analyses is done first using an assumption of homogenous preferences across smokers and non-smokers, and then it is relaxed to account for heterogeneous preferences between smokers and non-smokers as well as across various socio-economic factors. A variety of errors terms and probability weighting functions are used.

Expected Utility Theory

An initial simple analysis is displayed in Table II. It contains an EU model which uses a power utility function and a Contextual Utility (CU) error specification. The model estimates the parameters under the assumption that preferences are homogenous across the sample. The results account for clustering at the individual level, which occurs because subjects made 90 choices each in the risk preference task so the observations are not independent.

Risk aversion is found to be relatively high, which is indicated by the low value of r=0.446. The error term, μ, is found to be positive and statistically significant, which suggests that subjects did not act in a purely deterministic manner when completing the risk preference task but rather made behavioural errors, and therefore it is important to take this into account in all subsequent analyses.

TABLE II: EXPECTED UTILITY THEORY ML ESTIMATES
HOMOGENOUS PREFERENCES

	Model
	Power CU Error
Power function parameter (r)	0.446***
	(0.022)
Error (μ)	0.282***
	(0.011)
N	21150
log-likelihood	-13834.308

Results account for clustering at the individual level
Standard errors in parentheses
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

Table III displays an EU model with power utility and a CU error which relaxes the assumption of homogenous preferences. Preferences are allowed to vary across demographic, socio-economic, and smoking status characteristics. Additionally, there is a variable for whether the risk preference task was completed before the time preference task or vice versa.

TABLE III: EXPECTED UTILITY THEORY ML ESTIMATES
HETEROGENOUS PREFERENCES

	Model	
	Estimate	Std Error
Power function parameter (r)		
Age	-0.014**	0.006
White	0.108*	0.063
Male	0.120***	0.045
Commerce faculty	0.045	0.051
Financial aid	-0.053	0.045
Smoker	0.021	0.043
Constant	0.642***	0.129
Error (μ)		
Constant	0.277***	0.011
N	20700	
log-likelihood	-13474	

Results account for clustering at the individual level
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

Table III shows that a number of variables are statistically significant: older subjects are more risk averse and men are less risk averse than women. Additionally, white subjects are less risk averse than non-white subjects, although this is only significant at the 10% level. Of particular interest is that there are no statistically significant differences between smokers and non-smokers in this model.

Rank-Dependant Utility Theory

The previous EU models assume that there is no probability weighting; however, smokers could differ from non-smokers in their perception of probabilities. Thus in this section RDU models are used to account for potential differences in probability weighting.

In order to use RDU models one has to employ a PWF. One such PWF is the TK PWF described in (11). This paper will utilise two other common PWFs. The Prelec (1998) PWF uses two parameters, and is defined by:

$$\pi(p) = \exp[\,-\eta(-\ln p)^{\gamma}], \tag{22}$$

such that $\gamma > 0$, $\eta > 0$, and $0 < p < 1$. The Prelec PWF can achieve a broad range of functional forms: linear, S-shaped, and inverse S-shaped. The linear form describes the scenario where probabilities are accurately perceived. The S-shape form describes the scenario where low probabilities are underweighted and high probabilities are overweighted. The inverse S-shape form describes the scenario where low probabilities are overweighted and high probabilities are underweighted. It can also be purely concave or convex.

The power PWF is similar in form to the power utility function. It is expressed by:

$$\pi(p) = p^{\gamma}, \tag{23}$$

A notable feature of the power function is that while it can achieve concave, linear, and convex forms it cannot achieve an inverse S-shaped form, unlike the TK PWF or Prelec PWF.

Table IV displays estimates of RDU models assuming a power utility function, a CU error specification, homogenous preferences, and three PWFs. In Model 1 the hypothesis that the power PWF parameter γ is equal to 1 cannot be rejected (p=0.149) indicating a largely linear PWF. In Model 2 the TK PWF parameter γ is significantly less than 1 which indicates a PWF with an inverse S-shape.

TABLE IV: RANK-DEPENDENT UTILITY THEORY ML ESTIMATES
HOMOGENOUS PREFERENCES

	Model 1	**Model 2**	**Model 3**
	Power	TK	Prelec2
Power function parameter (r)	0.473***	0.598***	0.599***
	(0.019)	(0.026)	(0.026)
PWF parameter (γ)	1.069***	0.675***	0.583***
	(0.048)	(0.015)	(0.022)
PWF parameter (η)			0.999***
			(0.029)
Error (μ)	0.287***	0.237***	0.235***
	(0.012)	(0.008)	(0.008)
N	21150	21150	21150
log-likelihood	-13829.222	-13465.39	-13449.433

Results account for clustering at the individual level
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

In Model 3 the Prelec PWF parameter γ is significantly less than 1, while the η parameter is not statistically different to 1. This indicates that, similar to the TK PWF, the Prelec PWF has an inverse S-shape. Across all three models the *r* parameter indicates risk aversion, and is similar in magnitude to the corresponding parameter found in the EU models.

Table V displays two RDU models with a power utility function, a CU error specification, heterogeneous preferences, and two PWFs. The TK PWF and the Prelec PWF are used in order to further investigate the inverse S-shape probability weighting. In both models smokers and non-smokers are not statistically significantly different in their power utility function or PWFs. There are some differences across several other variables. For example, financial aid is a statistically significant explanatory variable of the power utility function in Model 1, but not Model 2.

Thus, regarding the differences between smokers and non-smokers, there is statistically significant evidence that probability weighting is of an inverse S-shaped form, but there is no statistically significant evidence that risk preferences differ between smokers and non-smokers.

TABLE V: RANK-DEPENDENT UTILITY THEORY ML ESTIMATES
HETEROGENOUS PREFERENCES

	Model 1		**Model 2**	
	TK		Prelec	
	Estimate	Std Error	Estimate	Std Error
Power function parameter (r)				
Age	-0.012	0.009	-0.008	0.009
White	0.042	0.072	-0.030	0.066
Male	0.117*	0.060	0.076	0.058
Commerce faculty	0.065	0.065	-0.007	0.060
Financial aid	-0.088	0.056	-0.113**	0.057
Smoker	0.032	0.054	0.011	0.053
Constant	0.779***	0.207	0.766***	0.190
PWF parameter (γ)				
Age	-0.006	0.007	-0.002	0.012
White	0.082*	0.045	0.079	0.055
Male	0.027	0.037	0.025	0.047
Commerce faculty	-0.018	0.034	-0.048	0.045
Financial aid	0.036	0.034	0.038	0.046
Smoker	-0.016	0.035	-0.017	0.048
Constant	0.768***	0.143	0.614**	0.255
PWF parameter (η)				
Age			0.015	0.013
White			-0.153**	0.063
Male			-0.080	0.070
Commerce faculty			-0.097*	0.056
Financial aid			-0.061	0.063
Smoker			-0.011	0.067
_cons			0.826***	0.289
Error (μ)				
Constant	0.234***	0.009	0.232***	0.008
N	20700		20700	
log-likelihood	-13096.4		-13064.3	

Results account for clustering at the individual level
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

b. Time Preferences: Smokers vs. Non-Smokers

Time preferences are analysed under the assumptions of linear utility, and by incorporating the curvature of the utility function identified by the risk preference task. Each of these analyses is done first using an assumption of homogenous preferences across smokers and non-smokers, and then it is relaxed to account for heterogeneous preferences between smokers and non-smokers as well as across various socio-economic factors. A variety of discount factors is used.

Risk Neutral Discounting

Four different discounting factors are used: Exponential as described in (13), Hyperbolic, Quasi-Hyperbolic, and Weibull. The exponential discount factor is time consistent, while the other three discount factors allow for time inconsistency. The other three are described below. Mazur’s (1984) Hyperbolic (H) discount factor is given by the following expression:

$$D^{H}(t) = 1 / (1 + \delta t), \tag{24}$$

The Quasi-Hyperbolic (QH) discount factor is:

$$D^{QH}(t) = 1 \qquad \text{If } t = 0 \tag{25a}$$

$$D^{QH}(t) = \beta / (1 + \delta)^{t}, \qquad \text{If } t > 0 \tag{25b}$$

The Weibull (WB) discount factor is:

$$D^{WB}(t) = \exp(-\delta t^{(1/\beta)}), \tag{26}$$

with $\beta > 0$ and $\delta > 0$.

Table VI displays four discounting models with a linear utility function, Fechner error term, homogenous preferences, and four discounting factors. All the models indicate high time preference, with the Hyperbolic model having unusually high coefficients and a low log-likelihood.

TABLE VI: DISCOUNTING FUNCTION ML ESTIMATES
LINEAR UTILITY AND HOMOGENOUS PREFERENCES

	Model 1	**Model 2**	**Model 3**	**Model 4**
	Exponential	Hyperbolic	Quasi-Hyperbolic	Weibull
Discounting parameter (δ)	3.635***	34.860***	2.645***	0.767***
	(0.234)	(2.280)	(0.171)	(0.029)
Discounting parameter (β)			0.928***	1.924***
			(0.004)	(0.044)
Error (ν)	41.061***	244.958***	40.681***	40.062***
	(2.579)	(15.996)	(2.418)	(2.277)
N	14100	14100	14100	14100
log-likelihood	-7512.467	-7752.028	-7121.229	-6829.21

Results account for clustering at the individual level
Standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Discounting with Concave Utility

Table VII displays four discounting models with a power utility function, Fechner error term, homogenous preferences, and four discounting factors. Comparing Table VI with Table VII it is apparent the relaxing of the assumption of a linear utility function led to substantially lower discount factor coefficients. The difference in results is to be expected given the general risk aversion which exists in the sample as displayed by Tables II and IV and the results of Andersen et al. (2008).[36]

TABLE VII: DISCOUNTING FUNCTION ML ESTIMATES
CONCAVE UTILITY AND HOMOGENOUS PREFERENCES

	Model 1	**Model 2**	**Model 3**	**Model 4**
	Exponential	Hyperbolic	Quasi-Hyperbolic	Weibull
Power function parameter (r)	0.447***	0.462***	0.441***	0.437***
	(0.022)	(0.022)	(0.021)	(0.021)
Discounting parameter (δ)	0.972***	0.767***	0.748***	0.325***
	(0.077)	(0.049)	(0.058)	(0.019)
Discounting parameter (β)			0.964***	2.019***
			(0.003)	(0.047)
Risk error (μ)	0.282***	0.279***	0.283***	0.284***
	(0.011)	(0.011)	(0.011)	(0.011)
Time error (ν)	0.777***	0.868***	0.748***	0.710***
	(0.137)	(0.154)	(0.130)	(0.122)
N	35250	35250	35250	35250
log-likelihood	-21325.938	-21239.493	-20889.889	-20570.476

Results account for clustering at the individual level
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Tables VIII:A and VIII:B display four discounting models with an EU function, Fechner error term, heterogeneous preferences, and four discounting factors. Being a smoker is found to be statistically significantly associated with high discount rates across all four models. For example, in Model 1 smokers discount at a 27 percentage point higher rate than non-smokers.

[36] The concave nature of most subjects' utility curves confounded the estimates of discounting parameters under the assumption of linear utility.

Several other statistically significant results include: being white or choosing over high principal options were associated with lower discount rates, while being in the commerce faculty or choosing over options with a FED were associated with higher discount rates.

TABLE VIII:A: DISCOUNTING FUNCTION ML ESTIMATES
CONCAVE UTILITY, HETEROGENOUS PREFERENCES

	Model 1 Exponential		**Model 2** Hyperbolic	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.005	0.003	-0.005	0.003
White	0.031	0.019	0.030	0.020
Male	-0.012	0.015	-0.012	0.016
Commerce faculty	0.046***	0.015	0.048***	0.016
Financial aid	-0.012	0.017	-0.012	0.018
Smoker	0.018	0.017	0.019	0.018
Constant	0.530***	0.072	0.551***	0.076
Discounting parameter (δ)				
Age	0.003	0.025	0.004	0.015
White	-0.300**	0.121	-0.193**	0.078
Male	-0.099	0.106	-0.068	0.067
Commerce faculty	0.230**	0.112	0.148**	0.068
Financial aid	-0.079	0.108	-0.050	0.068
FED: 1 week	0.056*	0.029	0.045**	0.019
High Principal	-0.161***	0.036	-0.105***	0.021
Smoker	0.268***	0.103	0.166**	0.066
Constant	0.930*	0.557	0.708**	0.333
Risk error (μ)				
Constant	0.278***	0.011	0.275***	0.011
Time error (ν)				
Constant	0.780***	0.140	0.886***	0.160
N	34500		34500	
log-likelihood	-20672.9		-20574.3	

Results account for clustering at the individual level
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

TABLE VIII:B: DISCOUNTING FUNCTION ML ESTIMATES
CONCAVE UTILITY, HETEROGENOUS PREFERENCES

	Model 3		**Model 4**	
	QHyp		Weibull	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.006*	0.003	-0.005*	0.003
White	0.025	0.019	0.016	0.016
Male	-0.009	0.014	-0.005	0.012
Commerce faculty	0.035**	0.014	0.031***	0.012
Financial aid	-0.009	0.016	-0.005	0.013
Smoker	0.017	0.016	0.013	0.013
Constant	0.548***	0.068	0.517***	0.059
Discounting parameter (δ)				
Age	-0.004	0.018	-0.001	0.005
White	-0.097	0.088	-0.070***	0.022
Male	-0.086	0.078	-0.011	0.020
Commerce faculty	0.171**	0.083	0.036*	0.020
Financial aid	-0.026	0.083	-0.015	0.020
FED: 1 week	0.692***	0.072	0.336***	0.022
High Principal	-0.068**	0.029	-0.028***	0.006
Smoker	0.156**	0.074	0.046**	0.020
Constant	0.338	0.394	0.191	0.117
Discounting parameter (β)				
Age	-0.001	0.001	0.075	0.139
White	0.024***	0.006	0.958*	0.521
Male	-0.004	0.005	0.164	0.382
Commerce faculty	0.002	0.005	-0.357	0.333
Financial aid	0.005	0.006	0.098	0.342
FED: 1 week	0.219***	0.069	1.745***	0.562
High Principal	0.010***	0.003	0.200	0.191
Smoker	-0.005	0.005	-0.691*	0.372
Constant	0.955***	0.03	2.335	2.974
Risk error (μ)				
Constant	0.280***	0.011	0.285***	0.012
Time error (ν)				
Constant	0.809***	0.142	0.579***	0.102
N	34500		34500	
log-likelihood	-19877.2		-19401.1	

Results account for clustering at the individual level
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

Discounting with probability weighted utility

Tables IX:A and IX:B displays four discounting models with an RDU function, Prelec PWF, Fechner error term, heterogeneous preferences, and four discounting factors. Being a smoker is statistically significantly associated with higher discounting parameters across all 4 models. For example, in Model 1 smokers discount at a 45 percentage point higher rate than non-smokers. Other results are generally similar to the results of the EU based models: variables White and High principal are associated with lower discounting parameters, and Commerce faculty and FED are associated with higher discounting parameters.

TABLE IX:A: DISCOUNTING FUNCTION ML ESTIMATES
RANK-DEPENDENT UTILITY AND HETEROGENOUS PREFERENCES

	Model 1		Model 2	
	Prelec Exp		**Prelec Hyp**	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.003	0.003	-0.003	0.003
White	0.025	0.021	0.025	0.022
Male	-0.027*	0.016	-0.028	0.017
Commerce faculty	0.049***	0.017	0.051***	0.018
Financial aid	-0.01	0.019	-0.009	0.02
Smoker	0.021	0.018	0.022	0.02
Constant	0.657***	0.076	0.724***	0.084
PWF parameter (γ)				
Age	-0.004	0.011	-0.004	0.011
White	0.062	0.054	0.059	0.052
Male	0.052	0.046	0.052	0.045
Commerce faculty	-0.064	0.045	-0.063	0.044
Financial aid	0.01	0.044	0.008	0.043
Smoker	-0.018	0.046	-0.018	0.046
Constant	0.661***	0.239	0.635***	0.235
PWF parameter (η)				
Age	0.018	0.012	0.019	0.013
White	-0.116*	0.062	-0.123*	0.065
Male	-0.159**	0.067	-0.166**	0.07
Commerce faculty	-0.061	0.056	-0.064	0.058
Financial aid	0.016	0.063	0.018	0.066
Smoker	-0.004	0.061	-0.004	0.063
Constant	0.771***	0.282	0.808***	0.296
Discounting parameter (δ)				
Age	0.004	0.042	0.005	0.022
White	-0.543***	0.196	-0.323***	0.118
Male	-0.138	0.173	-0.081	0.098
Commerce faculty	0.340*	0.187	0.196*	0.101
Financial aid	-0.125	0.175	-0.073	0.101
FED: 1 week	0.095*	0.051	0.080***	0.03
High Principal	-0.332***	0.074	-0.210***	0.042
Smoker	0.445***	0.171	0.246**	0.099
Constant	1.516	0.938	1.111**	0.502
Risk error (μ)				
Constant	0.233***	0.008	0.236***	0.009
Time error (ν)				
Constant	2.622***	0.543	4.134***	1.041
N	34500		34500	
log-likelihood	-20213		-20076.1	

Results account for clustering at the individual level
* p<0.10, ** p<0.05, *** p<0.01

TABLE IX:B: DISCOUNTING FUNCTION ML ESTIMATES
RANK-DEPENDENT UTILITY AND HETEROGENOUS PREFERENCES

	Model 3		**Model 4**	
	Prelec QH		**Prelec WB**	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.005	0.003	-0.004	0.003
White	0.014	0.021	0.011	0.017
Male	-0.021	0.015	-0.014	0.013
Commerce faculty	0.035**	0.015	0.031**	0.013
Financial aid	-0.009	0.017	-0.004	0.014
Smoker	0.022	0.017	0.014	0.014
Constant	0.670***	0.072	0.625***	0.064
PWF parameter (γ)				
Age	-0.004	0.011	-0.004	0.011
White	0.066	0.055	0.068	0.056
Male	0.050	0.046	0.05	0.047
Commerce faculty	-0.062	0.045	-0.062	0.046
Financial aid	0.011	0.045	0.011	0.046
Smoker	-0.019	0.047	-0.019	0.048
Constant	0.664***	0.244	0.676***	0.247
PWF parameter (η)				
Age	0.016	0.012	0.016	0.012
White	-0.121*	0.062	-0.122**	0.061
Male	-0.153**	0.065	-0.145**	0.064
Commerce faculty	-0.069	0.055	-0.07	0.054
Financial aid	0.017	0.062	0.021	0.061
Smoker	-0.003	0.060	-0.009	0.059
Constant	0.791***	0.272	0.759***	0.273
Discounting parameter (δ)				
Age	-0.001	0.028	-0.001	0.007
White	-0.163	0.125	-0.090***	0.028
Male	-0.130	0.114	-0.013	0.025
Commerce faculty	0.232*	0.122	0.043*	0.025
Financial aid	-0.036	0.122	-0.02	0.025
FED: 1 week	1.050***	0.118	0.389***	0.026
High Principal	-0.106**	0.046	-0.043***	0.008
Smoker	0.226**	0.109	0.059**	0.025
Constant	0.411	0.601	0.244	0.150
Discounting parameter (β)				
Age	-0.001	0.002	0.058	0.130
White	0.027***	0.009	0.901*	0.471
Male	-0.009	0.007	0.176	0.345
Commerce faculty	0.002	0.006	-0.282	0.296
Financial aid	0.006	0.009	0.102	0.322
FED: 1 week	0.249***	0.071	1.149***	0.430
High Principal	0.016***	0.004	0.209	0.187
Smoker	-0.003	0.007	-0.643*	0.340
Constant	0.930***	0.039	2.531	2.733
Risk error (μ)				
Constant	0.234***	0.008	0.235***	0.009
Time error (ν)				
Constant	2.377***	0.46	1.467***	0.269
N	34500		34500	
log-likelihood	-19433.9		-18977.2	

Results account for clustering at the individual level
* p<0.10, ** p<0.05, *** p<0.01

c. Risk Preferences, Time Preferences, and Smoking Intensity

Differences in risk preferences and time preferences according to smoking intensity were analysed similarly to risk preferences and time preferences between smokers and non-smokers. Two metrics were used to evaluate smoking intensity: FTND and a quadratic function of number of cigarettes smoked per day. This section will present a broad overview of the results.

Risk preferences

Table X displays two RDU models with a power utility function, the FTND metric, a CU error specification, heterogeneous preferences, and a Prelec PWF. The FTND metric is not statistically significantly related to the curvature of the utility function or to the PWF parameters. An EU model[37] (similar to that of Table X but with no PWF) has generally consistent findings to that of Table X with regard to risk preferences, and specifically, FTND remains statistically insignificant.

[37] This model appears in Appendix B: Table 1.

TABLE X: RANK-DEPENDENT UTILITY THEORY ML ESTIMATES
HETEROGENOUS PREFERENCES

	Model	
	Prelec	
	Estimate	Std Error
Power function parameter (ρ)		
Age	0.009	0.010
White	0.086	0.099
Male	-0.035	0.077
Commerce faculty	0.014	0.071
Financial aid	-0.141**	0.069
FTND	-0.015	0.018
Constant	0.522**	0.213
PWF parameter (γ)		
Age	-0.011	0.010
White	0.125*	0.065
Male	0.009	0.06
Commerce faculty	-0.098*	0.052
Financial aid	0.054	0.06
FTND	-0.006	0.013
Constant	0.829***	0.246
PWF parameter (η)		
Age	0.035*	0.018
White	-0.088	0.077
Male	-0.093	0.083
Commerce faculty	-0.046	0.067
Financial aid	-0.051	0.088
FTND	0.008	0.019
Constant	0.333	0.417
Error (μ)		
Constant	0.217***	0.009
N	12510	
log-likelihood	-7816.79	

Results account for clustering at the individual level
* p<0.10, ** p<0.05, *** p<0.01

Table XI displays two RDU models with a power utility function, the number of cigarettes quadratic metric, a CU error specification, heterogeneous preferences, and a PWF (TK for Model 1 and Prelec for Model 2). These models, in contrast to that of Table X (which did not find FTND to be statistically significant) finds number of cigarettes to be statistically significant in both models and number of cigarettes squared to be statistically significant in Model 1.

In both models a higher number of cigarettes smoked is associated with greater risk aversion. However, in Model 1 this relationship is found to be quadratic, and the greatest risk aversion (the peak of the parabola) is found at 13 cigarettes smoked per day. An EU model[38] (similar to that of Table XI but with no PWF) has generally consistent findings to that of Table XI with regard to risk preferences.

These models show that there is a relationship between smoking intensity and risk preferences, but that the exact nature of the relationship (whether it is linear or quadratic) may depend on the PWF specification. It may also be that with a larger sample size the quadratic term would be statistically significant in both models.

[38] This model is shown in Appendix B: Table 2.

TABLE XI: RANK-DEPENDENT UTILITY THEORY ML ESTIMATES
HETEROGENOUS PREFERENCES

	Model 1		Model	
	TK		Prelec	
	Estimate	Std Error	Estimate	Std Error
Power function parameter (r)				
Age	-0.008	0.010	0.006	0.011
White	0.176	0.109	0.115	0.092
Male	0.066	0.087	0.005	0.079
Commerce faculty	0.058	0.075	0.016	0.069
Financial aid	-0.092	0.071	-0.116*	0.068
Number of cigarettes	-0.052**	0.022	-0.042**	0.021
Number of cigarettes squared	0.002**	0.001	0.001	0.001
Constant	1.014***	0.268	0.722***	0.263
PWF parameter (γ)				
Age	-0.012**	0.005	-0.012	0.01
White	0.102	0.062	0.144**	0.065
Male	0.015	0.068	0.012	0.062
Commerce faculty	-0.050	0.041	-0.104**	0.052
Financial aid	0.040	0.042	0.061	0.060
Number of cigarettes	-0.002	0.016	-0.004	0.018
Number of cigarettes squared	0.000	0.001	0.000	0.001
Constant	0.932***	0.153	0.875***	0.238
PWF parameter (η)				
Age			0.033**	0.016
White			-0.110	0.086
Male			-0.083	0.083
Commerce faculty			-0.055	0.067
Financial aid			-0.051	0.08
Number of cigarettes			0.011	0.017
Number of cigarettes squared			0.000	0.001
Constant			0.339	0.400
Error (μ)				
Constant	0.217***	0.01	0.215***	0.009
N	12510		12510	
log-likelihood	-7812.198		-7785.95	

Results account for clustering at the individual level
* p<0.10, ** p<0.05, *** p<0.01

Time Preferences

Table XII displays two discounting models with an RDU function, FTND metric, Fechner error term, heterogeneous preferences, Prelec PWF, and two discounting factors (exponential and hyperbolic). The FTND metric is not statistically significantly related to the utility function or to the discounting parameters. Other discounting factors for the RDU model as well as a full EU model similar to that of Table XII[39] have generally consistent findings to that of Table XII with regard to the utility function and time preferences, and specifically that FTND has no statistically significant relationship to discounting parameters.

Table XIII displays two discounting models with an RDU function, the number of cigarettes quadratic metric, Fechner error term, heterogeneous preferences, Prelec PWF, and two discounting factors (exponential and hyperbolic). The cigarette metrics are not statistically significantly related to the discounting parameters. Other discounting factors for the EU model as well as a full RDU model similar to that of Table XIII[40] have generally consistent findings to that of Table XIII with regard to the utility function and time preferences, and specifically that the cigarette metrics have no statistically significant relationships to discounting parameters.

Table XII shows that the FTND metric does not correlate with time preferences, while Table X showed that FTND does not correlate with risk preferences. Number of cigarettes smoked per day does correlate with risk preferences (shown in Table XI), but does not correlate with time preferences (shown in table XIII). This shows that FTND and the number of cigarettes smoked per day are different measures of smoking intensity that have different relationships with risk preferences and time preferences.

[39] The RDU and EU model are shown in Appendix B: Table 3 and 4 (respectively).
[40] The RDU and EU models are shown in Appendix B: Table 5 and 6 (respectively).

TABLE XII: DISCOUNTING FUNCTION ML ESTIMATES
RANK-DEPENDENT UTILITY AND HETEROGENOUS PREFERENCES

	Model 1		Model 2	
	Exponential		Hypberbolic	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.002	0.004	-0.002	0.005
White	0.016	0.027	0.015	0.029
Male	-0.050**	0.023	-0.053**	0.024
Commerce faculty	0.055**	0.023	0.059**	0.025
Financial aid	-0.022	0.023	-0.022	0.025
FTND	-0.005	0.005	-0.005	0.005
Constant	0.697***	0.104	0.773***	0.115
PWF parameter (γ)				
Age	-0.010	0.011	-0.009	0.011
White	0.142**	0.066	0.139**	0.065
Male	0.010	0.057	0.012	0.056
Commerce faculty	-0.111**	0.052	-0.108**	0.051
Financial aid	0.029	0.057	0.028	0.055
FTND	-0.011	0.014	-0.010	0.014
Constant	0.836***	0.257	0.798***	0.255
PWF parameter (η)				
Age	0.024	0.016	0.026	0.018
White	-0.136*	0.078	-0.142*	0.081
Male	-0.111	0.086	-0.115	0.090
Commerce faculty	-0.022	0.071	-0.023	0.074
Financial aid	0.044	0.088	0.048	0.092
FTND	0.013	0.017	0.013	0.018
Constant	0.530	0.393	0.551	0.418
Discounting parameter (δ)				
Age	0.042	0.045	0.023	0.024
White	-0.113	0.270	-0.080	0.147
Male	-0.349	0.261	-0.180	0.135
Commerce faculty	0.545**	0.248	0.292**	0.127
Financial aid	-0.066	0.304	-0.032	0.154
FED: 1 week	0.095	0.07	0.080**	0.039
High Principal	-0.318***	0.096	-0.200***	0.050
FTND	0.035	0.066	0.019	0.033
Constant	0.920	1.065	0.839	0.570
Risk error (μ)				
Constant	0.219***	0.009	0.221***	0.010
Time error (ν)				
Constant	2.456***	0.627	3.923***	1.199
N	20850		20850	
log-likelihood	-11965.98		-11868.92	

Results account for clustering at the individual level
* p<0.10, ** p<0.05, *** p<0.01

TABLE XIII: DISCOUNTING FUNCTION ML ESTIMATES
RANK-DEPENDENT UTILITY AND HETEROGENOUS PREFERENCES

	Model 1		Model 2	
	Exponential		Hyperbolic	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.001	0.004	-0.001	0.004
White	0.033	0.028	0.032	0.030
Male	-0.056***	0.020	-0.059***	0.021
Commerce faculty	0.059***	0.022	0.064***	0.024
Financial aid	-0.012	0.026	-0.012	0.028
Number of Cigarettes	-0.010*	0.006	-0.010*	0.006
Number of cigarettes squared	0.000	0.000	0.000	0.000
Constant	0.703***	0.096	0.777***	0.108
PWF parameter (γ)				
Age	-0.012	0.010	-0.011	0.010
White	0.164**	0.064	0.161**	0.063
Male	0.032	0.058	0.034	0.056
Commerce faculty	-0.118**	0.051	-0.115**	0.050
Financial aid	0.035	0.058	0.034	0.057
Number of Cigarettes	-0.013	0.018	-0.012	0.018
Number of cigarettes squared	0.000	0.001	0.000	0.001
Constant	0.930***	0.241	0.889***	0.238
PWF parameter (η)				
Age	0.026*	0.015	0.028*	0.016
White	-0.169*	0.09	-0.178*	0.094
Male	-0.129	0.081	-0.132	0.084
Commerce faculty	-0.028	0.071	-0.029	0.074
Financial aid	0.028	0.082	0.030	0.086
Number of Cigarettes	0.031**	0.015	0.033**	0.016
Number of cigarettes squared	-0.001*	0.001	-0.001*	0.001
Constant	0.381	0.383	0.393	0.405
Discounting parameter (δ)				
Age	0.031	0.040	0.018	0.022
White	-0.283	0.291	-0.181	0.161
Male	-0.357	0.243	-0.187	0.129
Commerce faculty	0.532**	0.253	0.290**	0.130
Financial aid	-0.111	0.276	-0.063	0.145
FED: 1 week	0.096	0.067	0.084**	0.038
High Principal	-0.324***	0.097	-0.209***	0.049
Number of Cigarettes	0.030	0.052	0.023	0.028
Number of cigarettes squared	0.000	0.002	0.000	0.001
Constant	1.036	1.000	0.841	0.542
Risk error (μ)				
Constant	0.218***	0.009	0.219***	0.010
Time error (ν)				
Constant	2.442***	0.642	3.956***	1.235
N	20850		20850	
log-likelihood	-11920.51		-11820.5	

Results account for clustering at the individual level
* p<0.10, ** p<0.05, *** p<0.01

Section 6: Discussion

There are two primary aspects of this research to discuss: smoking status, and smoking intensity. The results of smoking status will be discussed primarily in comparison to Harrison et al. (2018), as this dissertation sought to replicate the methods and analysis of that paper.[41] The results of smoking intenstiy represent an extension beyond both Harrison et al. (2018) and the rest of the literature.

This paper analysed data produced by subjects who engaged in incentive-compatible experiments. The data were analysed using maximum likelihood estimation in order to avoid the pitfall – common in much of the literature – of treating point estimates as data during a second round of analysis. Both EU and RDU specifications were investigated. Various PWFs and discounting factors were used.

I did not find smoking status to have any relationship with risk preferences across a range of specifications. This relationship replicates that which was found in Harrison et al. (2018). The literature is equivocal on the relationship between risk preferences and smoking status. However, much of the literature uses flawed experimental designs and flawed statistical methods, as expounded upon in the literature review.

Across a range of specifications I found that smoking status was correlated with greater discounting. This relationship replicates that which was found in Harrison et al. (2018) and is broadly in line with the literature generally.

I found that smoking intensity had a statistically significant relationship with risk preferences. This relationship was found when the smoking metric used was a number of cigarettes smoked quadratic, but not when the metric used was FTND. The turning point for quadratic

[41] It is worth noting that Harrison et al. (2018) had a sample of 175 individuals, while this paper has a sample of 235. Thus, while differences may be attributable to different samples, they may also be attributable to a difference in statistical power.

was 13 cigarettes per day – people who smoke 13 cigarettes per day tend to be more risk-loving than people who smoke more than or less than them.

Of the little research on the relationship between smoking intensity and risk preferences, all other research fails to find a significant relationship between smoking intensity and risk preferences. There may be several reasons why this experiment departs from the norm: experimental design (this dissertation has real rewards as opposed to hypothetical rewards); sample size (this dissertation has a relatively large size as opposed to the typically small samples of studies which use real rewards); smoking intensity metric (this dissertation used both FTND and number of cigarettes smoked, whereas other studies often only use one metric); and others, as discussed in detail in the literature review. It may also just be the sample – a replication of this dissertation is necessary to see whether the results are specific to the sample.

Across a range of specifications this dissertation did not find smoking intensity to have any relationship with discounting. This occurs across both metrics for smoking intensity. By contrast, most other research finds greater smoking intensity to be correlated with greater discounting, albeit Harrison et al. (2018) found a parabolic relationship.

It should be noted that other studies of smoking intensity have had samples with a higher mean number of cigarettes smoked. In this dissertation smokers had a mean of 8.90 cigarettes smoked per day. By comparison, for example, Ohmura (2005) smokers had a mean of 14.38 cigarettes smoked per day, while in Reynolds et al. (2004) all smokers had a minimum of 20 cigarettes smoked per day. There is a similar situation when comparing results to studies such as Ida and Goto (2009) and Ida (2009) where FTND was used to measure smoking intensity – heavy smokers were rarer in this study than others occurring in the literature. The lower smoking intensity in this study may explain why this study has different findings with regard to the relationship between time preferences and smoking intensity compared to other studies in the literature.

Section 7: Conclusion

This dissertation set out to investigate how risk preferences and time preferences relate to tobacco use. The primary findings are that: smokers discount more than non-smokers; smokers do not differ on risk preferences compared to non-smokers; smoking intensity has no relationship with time preferences; and, smoking intensity is correlated with risk preferences, such that greater smoking intensity is associated with lower risk aversion (although the relationship appears to be quadratic, with very heavy smokers being more risk averse than heavy smokers).

This dissertation has a number of limitations: the sample is primarily students (and thus the findings may not generalise to the entire population); there were few heavy smokers relative to other studies on smoking intensity; the study has a South African sample (and thus the findings may not generalise to significantly richer or poorer countries).

The findings of this dissertation regarding the difference between smokers and non-smokers replicate findings common in the literature. The findings regarding smoking intensity differ from the findings common in the literature. These differences may occur because of the paucity of research in this area, differences in statistical methods or experimental design, or due to the idiosyncratic nature of the sample used in this dissertation.

From a public policy perspective, given that smokers discount more than non-smokers, programmes which highlight the long run (or delayed) costs of smoking (e.g., health advisories) may not be highly effective, while policies which increase the short run (or immediate) costs of smoking (e.g., taxes on cigarettes) are likely to be relatively more effective. An intervention targeting heavier smokers could benefit from the knowledge that heavier smokers tend to be less risk averse by focusing the intervention on social spaces renowned for low risk aversion (such as casinos or horse racecourses) instead of areas renowned for moderate or high risk aversion.

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Appendix A: Risk preference task instructions

Task Instructions

This is a task where you will choose between lotteries with varying prizes and chances of winning. On each computer screen you will be presented with a pair of lotteries and you will need to choose one of them. There are 90 pairs of lotteries in this task. For each pair of lotteries, you should choose the lottery you prefer to play. You will actually get the chance to play **one** of the lotteries you choose, and you will be paid according to the outcome of that lottery, so you should think carefully about which lottery you prefer.

Here is an example of what the computer display of such a pair of lotteries might look like.

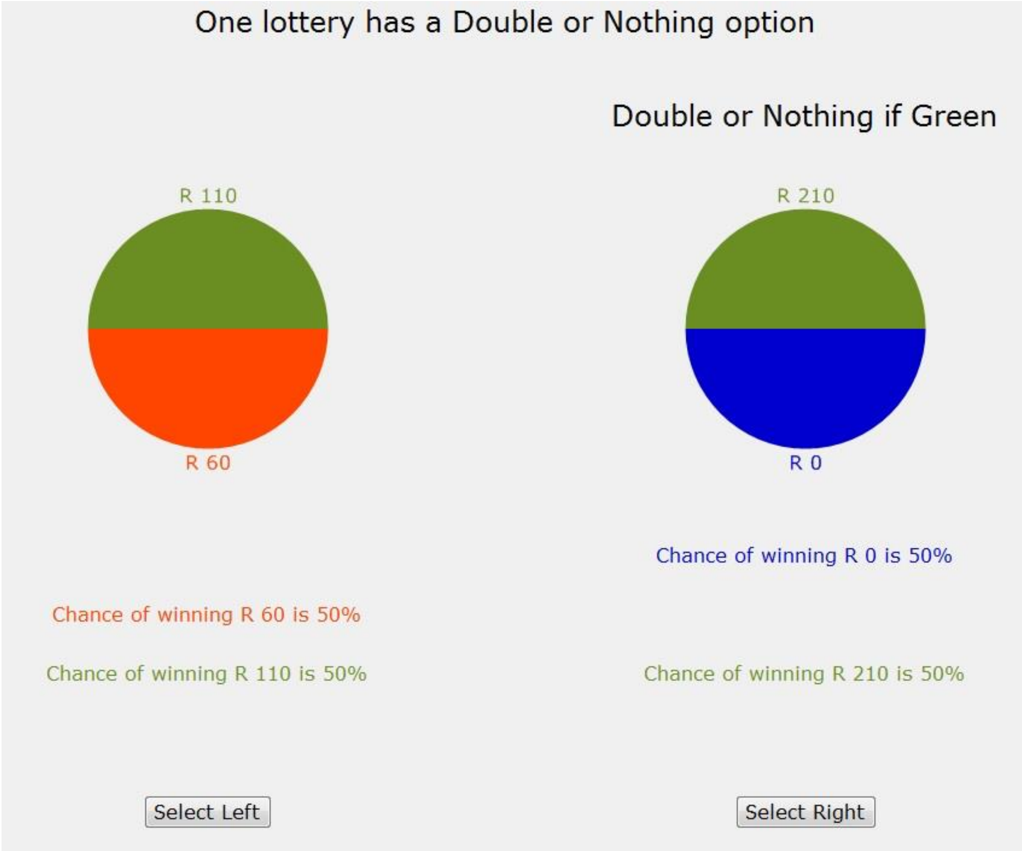
The outcome of the lotteries will be determined by the draw of a random number between 1 and 100. Each number between, and including, 1 and 100 is equally likely to occur. In fact, you will be able to draw the number yourself using two 10-sided dice.

In the above example, the Left lottery pays R20 with a 55% chance, R160 with a 25% chance and R190 with a 20% chance. So when you roll the two 10-sided dice if the number drawn is between 1 and 55 you will be paid R20, if the number is between 56 and 80 you will be paid R160, and if the number is between 81 and 100 you will be paid R190. The blue colour in the pie chart corresponds to 55% of the area and illustrates the chances that the number drawn will be between 1 and 55 and your prize will be R20. The orange area in the pie chart corresponds to 25% of the area and illustrates the chances that the number drawn will be between 56 and 80 and your prize will be R160. The green area in the pie chart corresponds to 20% of the area and illustrates the chances that the number drawn will be between 81 and 100 and your prize will be R190.

Now look at the Right lottery in the example. It pays R20 with a 75% chance, and R250 with a 25% chance. So when you roll the two 10-sided dice if the number drawn is between 1 and 75 you will be paid R20, and if the number is between 76 and 100 you will be paid R250. The blue colour in the pie chart corresponds to 75% of the area and illustrates the chances that the number drawn will be between 1 and 75 and your prize will be R20. The green area in the pie chart corresponds to 25% of the area and illustrates the chances that the number drawn will be between 76 and 100 and your prize will be R250.

Each pair of lotteries is shown on a separate screen on the computer. On each screen, you should indicate which lottery you prefer to play by clicking on one of the buttons beneath the lotteries.

You could also get a pair of lotteries in which one of the lotteries will give you the chance to play "Double or Nothing." For instance, the Right lottery in the following screen image pays "Double or Nothing" if the Green area is selected. The right pie chart indicates that there is a 50% chance that you get R0. So if you roll the two 10-sided dice and the number drawn is between 1 and 50 you will be paid R0. However, if the number is between 51 and 100 you will toss a coin to determine if you get double the amount listed in green (R210). If the coin comes up Heads you get R420, otherwise you get nothing. The prizes listed underneath each pie refer to the amounts before any "Double or Nothing" coin toss.

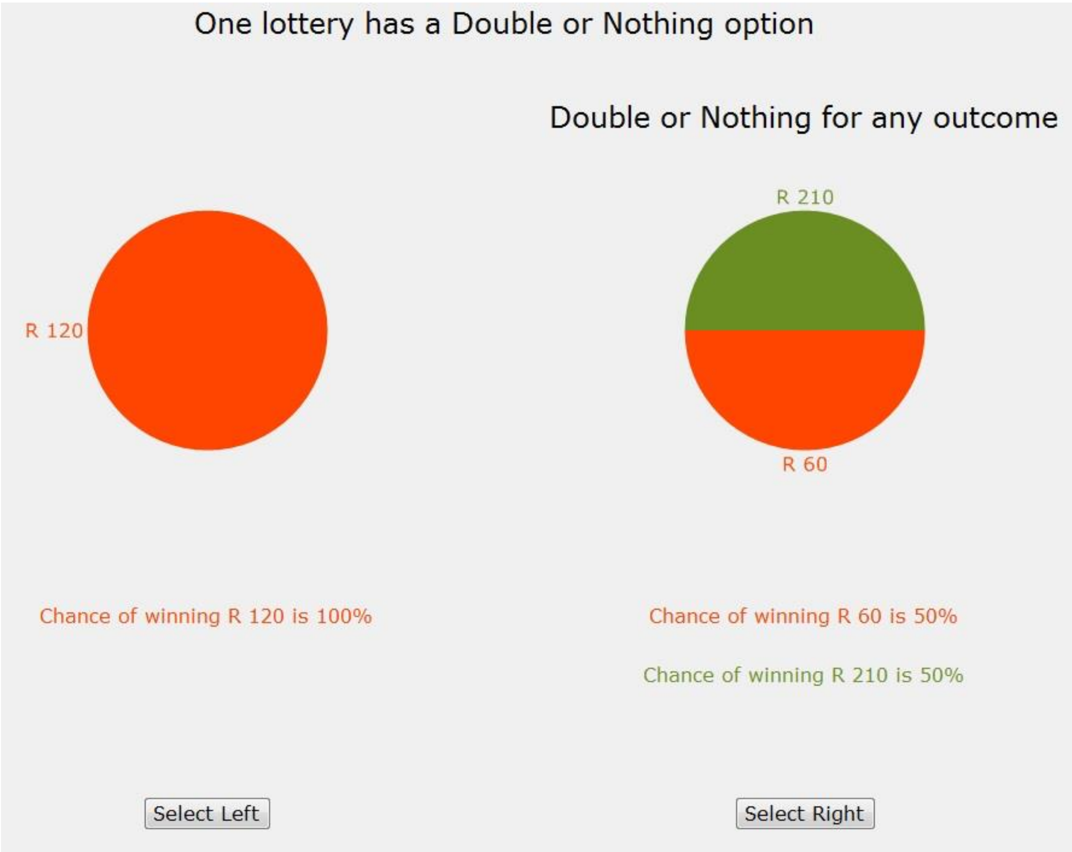


For instance, suppose you picked the lottery on the left in the last example. If the random number drawn was 37, you would win R60; if it was 93, you would get R110.

If you picked the lottery on the right and drew the number 37, you would get R0; if instead you drew 93, you would have to toss a coin to determine if you get "Double or Nothing." If the coin comes up Heads then you get R420. However, if it comes up Tails you get nothing from your chosen lottery.

After you have worked through all of the 90 pairs of lotteries, raise your hand and an experimenter will come to you to determine your payment for this task. You will roll two 10-sided dice until a number between 1 and 90 comes up to determine which pair of lotteries will be played out. Since there is a chance that any of your 90 choices could be played out for real, you should approach each pair of lotteries as if it is the one that you will play out. Finally, you will roll the two ten-sided dice again to determine the outcome of the lottery you chose, and if necessary you will then toss a coin to determine if you get "Double or Nothing."

It is also possible that you will be given a lottery in which there is a "Double or Nothing" option no matter what number you roll with the two 10-sided dice. The screen image below illustrates this possibility. The Right lottery in the example pays "Double or Nothing" for any number that is drawn with the two 10-sided dice. So if you select the Right lottery and roll a number between 1 and 50 you will toss a coin to see whether you get R0 or R120 (double R60). If you roll a number between 51 and 100 you will toss a coin to see whether you get R0 or R420 (double R210).



Therefore, your earnings for this task are determined by four things:

- by which lottery you selected, the Left or the Right, for each of these 90 pairs;
- by which lottery pair is chosen to be played out in the set of 90 such pairs using the two 10-sided dice;
- by the outcome of that lottery when you roll the two 10-sided dice; and
- by the outcome of a coin toss if the chosen lottery outcome is of the "Double or Nothing" type.

Which lotteries you prefer is a matter of personal taste. The people next to you may be presented with different lotteries, and may have different preferences, so their responses should not matter to you. Please work silently, and make your choices by thinking carefully about each lottery.

Payment for this task is in cash, and is in addition to the R40 show-up fee that you receive just for being here. When you have finished the task, please raise your hand and an experimenter will come to you to determine your payment for this task.

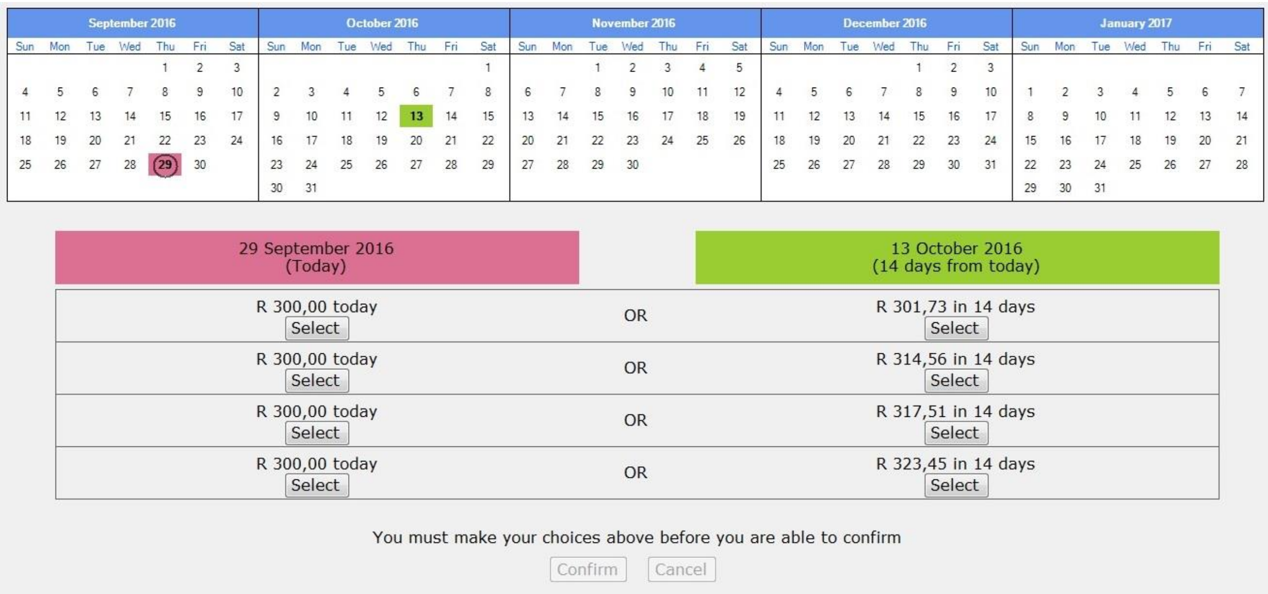
Please raise your hand now

Appendix A: Time preference task instructions

Task Instructions

In this task you will choose between different amounts of money available at different times. You will need to make 60 choices in total. For each choice you will decide between a smaller amount of money which is available sooner and a larger amount of money which is available later. One of your 60 choices will be selected at random for payment and you will receive the amount of money you chose at the appropriate date.

All of these choices will be made on a computer and here is an example of what the computer display might look like:



For the purpose of explaining this task, assume for the moment that today is 29 September, 2016. At the top of the display is a calendar showing you today's date in a circle (29 September 2016). This date is also highlighted in purple and a future date is highlighted in green (13 October 2016). Below the calendar are two columns: a purple column with amounts of money available at an earlier date (today) and a green column with amounts of money available at a later date (in 14 days from today). You need to make 4 choices on this screen. Each choice appears on a different row.

In the first row, you need to choose between receiving R300 today or R301.73 in 14 days from today. Note that R300 is the smaller of the two amounts but it is available today. R301.73 is the larger of the two amounts but it is only available after 14 days. Suppose that you prefer R300 today over R301.73 in 14 days from today. To choose R300 today just click the button saying "Select" under "R300 today".

Suppose instead that you prefer R301.73 in 14 days rather than R300 today. To choose R301.73 in 14 days just click the button saying “Select” under “R301.73 in 14 days”.
Once you have made your choice on the first row you can move on to the other rows on the screen. You need to make 4 choices on the screen before you can move on to the next set of 4 choices on a new screen. Once you have made all of your choices on the screen you can click the button saying “Confirm” to move on to the next screen. If you would like to change your choices then click “Cancel”.

You will need to make 60 choices in total across 15 screens. The rand amounts change on each row of each screen. In addition, the times for delivery of the rand amounts change <u>across</u> screens. For example, on the screen we just looked at, you had to choose between an amount of money available today and an amount of money available in 14 days. On a different screen, you may need to choose between an amount of money available in 7 days and another amount of money available in 21 days. So please pay careful attention when making your choices.

When you are finished the task, please raise your hand and an experimenter will come to you to determine your payment for this task. You will select one of the 15 screens from this task by rolling a 20-sided dice. If the dice lands on 1, you will select screen 1; if the dice lands on 7, you will select screen 7; if the dice lands on 12, you will select screen 12; and so on. If the dice lands on 16, 17, 18, 19 or 20, you will roll the dice again until it lands on a number between 1 and 15.

Once you have selected a screen, you will roll a 4-sided dice to select 1 of the 4 rows on the screen. If the dice lands on 1, you will select row 1; if the dice lands on 2, you will select row 2; and so on. Once you have selected the row, we will look at the choice that you made on that row. You will then be paid for the choice that you made on that row on the date listed for that choice. For instance, in the last example, suppose that row 3 is selected for payment. If you chose R300 today, you will be paid R300 at the end of today’s session. If you chose R317.51 in 14 days then you will be paid R317.51 in 14 days via electronic transfer into your bank account and you will receive a payment notification on your cellphone when the transaction has taken place. That is why we need your bank account details: to pay you via electronic transfer, if necessary.

Note that the option you prefer on each row is a matter of personal taste. The people next to you may have different tastes so their choices should not matter for you. Please work silently and make your choices by thinking carefully about each option. Since there is a chance that any of your 60 choices could be selected for payment, you should approach each choice as if it is the one that you will be paid for.

Please raise your hand now

Appendix B: Table 1

TABLE 1: EXPECTED UTILITY THEORY ML ESTIMATES
HETEROGENOUS PREFERENCES

	Model	
	Estimate	Std Error
Power function parameter (r)		
Age	-0.012*	0.006
White	0.205**	0.094
Male	0.038	0.063
Commerce faculty	0.016	0.067
Financial aid	-0.084	0.062
FTND	-0.019	0.015
Constant	0.748***	0.154
Error (μ)		
Constant	0.261***	0.012
N	12510	
log-likelihood	-8094.047	

Results account for clustering at the individual level
* p<0.10, ** p<0.05, *** p<0.01

Appendix B: Table 2

TABLE 2: EXPECTED UTILITY THEORY ML ESTIMATES
HETEROGENOUS PREFERENCES

	Model	
	Estimate	Std Error
Power function parameter (r)		
Age	-0.019***	0.006
Male	0.116**	0.057
Commerce faculty	0.01	0.07
Number of cigarettes	-0.052***	0.019
Number of cigarettes squared	0.002**	0.001
Constant	1.082***	0.184
Error (μ)		
Constant	0.265***	0.013
N	12510	
log-likelihood	-8115.631	

Results account for clustering at the individual level
* p<0.10, ** p<0.05, *** p<0.01

Appendix B: Table 3

TABLE 3: DISCOUNTING FUNCTION ML ESTIMATES
RANK-DEPENDENT UTILITY AND HETEROGENOUS PREFERENCES

	Model 3		**Model 4**	
	Quasi-Hyperbolic		Weibull	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.003	0.004	-0.003	0.003
White	0.013	0.026	0.006	0.021
Male	-0.048**	0.019	-0.032*	0.016
Commerce faculty	0.040*	0.021	0.036**	0.018
Financial aid	-0.021	0.02	-0.008	0.017
FTND	-0.004	0.005	-0.006	0.004
Constant	0.693***	0.087	0.651***	0.073
PWF parameter (γ)				
Age	-0.01	0.011	-0.01	0.011
White	0.143**	0.067	0.149**	0.069
Male	0.009	0.058	0.005	0.06
Commerce faculty	-0.109**	0.053	-0.112**	0.055
Financial aid	0.029	0.058	0.029	0.059
FTND	-0.011	0.014	-0.011	0.015
Constant	0.846***	0.259	0.865***	0.264
PWF parameter (η)				
Age	0.023	0.016	0.022	0.016
White	-0.137*	0.077	-0.140*	0.076
Male	-0.11	0.085	-0.097	0.084
Commerce faculty	-0.032	0.071	-0.035	0.069
Financial aid	0.045	0.088	0.055	0.086
FTND	0.013	0.017	0.012	0.017
Constant	0.543	0.387	0.521	0.381
Discounting parameter (δ)				
Age	0.025	0.032	0.006	0.007
White	-0.024	0.182	-0.028	0.045
Male	-0.297	0.181	-0.06	0.074
Commerce faculty	0.328*	0.168	0.058	0.037
Financial aid	-0.092	0.196	-0.027	0.07
FED: 1 week	1.174***	0.154	0.389***	0.036
High Principal	-0.051	0.065	-0.044***	0.012
FTND	0.023	0.043	0.007	0.012
Constant	-0.014	0.734	0.151	0.158
Discounting parameter (β)				
Age	0	0.002	-0.057	0.053
White	0.009	0.01	0.249	0.571
Male	-0.017	0.011	0.831	0.914
Commerce faculty	0.002	0.009	-0.292	0.507
Financial aid	-0.01	0.012	0.502	1.044
FED: 1 week	0.277***	0.096	1.211*	0.657
High Principal	0.022***	0.006	0.114	0.29
FTND	-0.001	0.002	-0.059	0.141
Constant	0.909***	0.048	4.132***	1.367
Risk error (μ)				
Constant	0.219***	0.009	0.221***	0.009
Time error (ν)				
Constant	2.415***	0.572	1.433***	0.32
N	20850		20850	
log-likelihood	-11438.076		-11153.043	

Results account for clustering at the individual level
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

Appendix B: Table 4

TABLE 4:A: DISCOUNTING FUNCTION ML ESTIMATES
CONCAVE UTILITY, HETEROGENOUS PREFERENCES AND HOMOSCEDASTIC ERRORS

	Model 1 Exponential		**Model 2** Hyperbolic	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.005	0.005	-0.006	0.005
White	0.027	0.024	0.027	0.025
Male	-0.040*	0.021	-0.042*	0.022
Commerce faculty	0.048**	0.021	0.051**	0.022
Financial aid	-0.026	0.023	-0.027	0.024
FTND	-0.007	0.005	-0.007	0.005
Constant	0.623***	0.102	0.653***	0.108
Discounting parameter (δ)				
Age	0.03	0.03	0.018	0.018
White	-0.042	0.175	-0.033	0.104
Male	-0.257	0.169	-0.152	0.096
Commerce faculty	0.374**	0.16	0.224**	0.092
Financial aid	-0.037	0.192	-0.019	0.109
FED: 1 week	0.062	0.043	0.049*	0.026
High Principal	-0.164***	0.051	-0.106***	0.028
FTND	0.018	0.041	0.01	0.023
Constant	0.584	0.697	0.531	0.414
Risk error (μ)				
Constant	0.264***	0.013	0.261***	0.012
Time error (ν)				
Constant	0.860***	0.2	0.989***	0.234
N	20850		20850	
log-likelihood	-12286.094		-12212.851	

Results account for clustering at the individual level
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

TABLE 4:B: DISCOUNTING FUNCTION ML ESTIMATES
CONCAVE UTILITY, HETEROGENOUS PREFERENCES AND HOMOSCEDASTIC ERRORS

	Model 3		**Model 4**	
	Quasi-Hyperbolic		Weibull	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.005	0.004	-0.005	0.003
White	0.025	0.023	0.014	0.019
Male	-0.038**	0.018	-0.026*	0.015
Commerce faculty	0.035*	0.02	0.032**	0.016
Financial aid	-0.023	0.02	-0.012	0.016
FTND	-0.006	0.005	-0.007	0.004
Constant	0.621***	0.087	0.581***	0.073
Discounting parameter (δ)				
Age	0.014	0.022	0.005	0.006
White	0.017	0.134	-0.022	0.037
Male	-0.219*	0.127	-0.05	0.062
Commerce faculty	0.246**	0.122	0.050*	0.031
Financial aid	-0.059	0.134	-0.02	0.06
FED: 1 week	0.812***	0.101	0.348***	0.03
High Principal	-0.038	0.045	-0.031***	0.009
FTND	0.012	0.03	0.005	0.01
Constant	0.077	0.511	0.111	0.129
Discounting parameter (β)				
Age	-0.001	0.002	-0.058	0.062
White	0.011	0.008	0.224	0.632
Male	-0.01	0.009	0.854	0.997
Commerce faculty	0.001	0.007	-0.385	0.599
Financial aid	-0.007	0.009	0.499	1.198
FED: 1 week	0.250***	0.095	1.671	1.047
High Principal	0.015***	0.005	0.113	0.301
FTND	-0.001	0.002	-0.047	0.164
Constant	0.949***	0.042	4.265***	1.515
Risk error (μ)				
Constant	0.266***	0.013	0.271***	0.013
Time error (ν)				
Constant	0.934***	0.213	0.651***	0.146
N	20850		20850	
log-likelihood	-11750.88		-11454.494	

Results account for clustering at the individual level
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

Appendix B: Table 5

TABLE 5: DISCOUNTING FUNCTION ML ESTIMATES
RANK-DEPENDENT UTILITY AND HETEROGENOUS PREFERENCES

	Model 3		**Model 4**	
	Prelec2QH		**Prelec2 WB**	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.002	0.003	-0.002	0.003
White	0.026	0.026	0.017	0.021
Male	-0.053***	0.018	-0.037***	0.014
Commerce faculty	0.045**	0.021	0.039**	0.017
Financial aid	-0.015	0.021	-0.007	0.018
Number of cigarettes	-0.009	0.006	-0.007*	0.004
Number of cigarettes squared	0.000	0.000	0.000	0.000
Constant	0.704***	0.085	0.643***	0.065
PWF parameter (γ)				
Age	-0.012	0.010	-0.012	0.010
White	0.167**	0.066	0.173**	0.067
Male	0.030	0.059	0.027	0.061
Commerce faculty	-0.117**	0.052	-0.120**	0.053
Financial aid	0.036	0.059	0.036	0.060
Number of cigarettes	-0.014	0.019	-0.014	0.019
Number of cigarettes squared	0.000	0.001	0.000	0.001
Constant	0.942***	0.243	0.964***	0.247
PWF parameter (η)				
Age	0.024	0.015	0.024	0.015
White	-0.173*	0.089	-0.175**	0.088
Male	-0.127	0.080	-0.114	0.079
Commerce faculty	-0.037	0.070	-0.040	0.069
Financial aid	0.025	0.081	0.031	0.080
Number of cigarettes	0.032**	0.015	0.032**	0.015
Number of cigarettes squared	-0.001*	0.001	-0.001*	0.001
Constant	0.401	0.374	0.364	0.369
Discounting parameter (δ)				
Age	0.019	0.030	0.004	0.006
White	-0.072	0.191	-0.059	0.046
Male	-0.312*	0.173	-0.061	0.056
Commerce faculty	0.330**	0.166	0.054	0.038
Financial aid	-0.084	0.186	-0.035	0.058
FED: 1 week	1.157***	0.157	0.390***	0.039
High Principal	-0.044	0.066	-0.039***	0.011
Number of cigarettes	0.003	0.047	0.007	0.010
Number of cigarettes squared	0.001	0.002	0.000	0.000
Constant	0.107	0.728	0.153	0.154
Discounting parameter (β)				
Age	0.000	0.002	-0.051	0.064
White	0.016	0.012	0.599	0.576
Male	-0.017	0.012	0.968	0.772
Commerce faculty	0.003	0.008	-0.247	0.509
Financial aid	-0.006	0.013	0.648	0.891
FED: 1 week	0.272***	0.098	1.053**	0.529
High Principal	0.022***	0.006	0.037	0.259
Number of cigarettes	-0.003	0.003	-0.096	0.171
Number of cigarettes squared	0.000	0.000	0.002	0.007
Constant	0.925***	0.050	4.389**	1.836
Risk error (μ)				
Constant	0.218***	0.009	0.219***	0.010
Time error (ν)				
Constant	2.352***	0.562	1.435***	0.329
N	20850		20850	
log-likelihood	-11393.724		- 11103.698	

Results account for clustering at the individual level
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

Appendix B: Table 6

TABLE 6:A: DISCOUNTING FUNCTION ML ESTIMATES
CONCAVE UTILITY, HETEROGENOUS PREFERENCES AND HOMOSCEDASTIC ERRORS

	Model 1 Exponential		**Model 2** Hyperbolic	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.004	0.004	-0.005	0.005
White	0.046*	0.026	0.045*	0.028
Male	-0.043**	0.018	-0.046**	0.019
Commerce faculty	0.051**	0.021	0.054**	0.022
Financial aid	-0.016	0.025	-0.017	0.027
Number of Cigarettes	-0.012**	0.006	-0.012**	0.006
Number of cigarettes squared	0.000*	0.000	0.000*	0.000
Constant	0.641***	0.099	0.670***	0.107
Discounting parameter (δ)				
Age	0.024	0.029	0.016	0.018
White	-0.142	0.190	-0.097	0.115
Male	-0.266*	0.161	-0.158*	0.093
Commerce faculty	0.368**	0.163	0.222**	0.094
Financial aid	-0.055	0.176	-0.032	0.102
FED: 1 week	0.064	0.042	0.053**	0.025
High Principal	-0.167***	0.052	-0.111***	0.028
Number of Cigarettes	0.012	0.035	0.011	0.020
Number of cigarettes squared	0.000	0.001	0.000	0.001
Constant	0.672	0.682	0.542	0.411
Risk error (μ)				
Constant	0.262***	0.013	0.260***	0.013
Time error (ν)				
Constant	0.858***	0.201	0.992***	0.237
N	20850		20850	
log-likelihood	-12262.218		-12187.115	

Results account for clustering at the individual level

* p<0.10, ** p<0.05, *** p<0.01

TABLE 6:B: DISCOUNTING FUNCTION ML ESTIMATES
CONCAVE UTILITY, HETEROGENOUS PREFERENCES AND HOMOSCEDASTIC ERRORS

	Model 3		**Model 4**	
	Quasi-Hyperbolic		Weibull	
	Estimate	Std error	Estimate	Std error
Power function parameter (r)				
Age	-0.005	0.004	-0.004	0.003
White	0.041*	0.025	0.026	0.020
Male	-0.040**	0.017	-0.029**	0.012
Commerce faculty	0.040**	0.019	0.035**	0.016
Financial aid	-0.016	0.021	-0.010	0.017
Number of Cigarettes	-0.011*	0.006	-0.009**	0.004
Number of cigarettes squared	0.000*	0.000	0.000*	0.000
Constant	0.643***	0.087	0.581***	0.066
Discounting parameter (δ)				
Age	0.010	0.021	0.004	0.005
White	-0.006	0.140	-0.045	0.039
Male	-0.229*	0.123	-0.051	0.048
Commerce faculty	0.247**	0.121	0.047	0.031
Financial aid	-0.048	0.128	-0.025	0.049
FED: 1 week	0.803***	0.102	0.348***	0.032
High Principal	-0.036	0.045	-0.027***	0.009
Number of Cigarettes	-0.007	0.034	0.005	0.008
Number of cigarettes squared	0.001	0.001	0.000	0.000
Constant	0.186	0.509	0.112	0.128
Discounting parameter (β)				
Age	-0.001	0.002	-0.053	0.075
White	0.019**	0.009	0.573	0.660
Male	-0.010	0.009	1.015	0.854
Commerce faculty	0.001	0.007	-0.352	0.613
Financial aid	-0.003	0.010	0.642	1.026
FED: 1 week	0.241**	0.096	1.467	0.926
High Principal	0.015***	0.005	0.020	0.282
Number of Cigarettes	-0.003	0.003	-0.085	0.180
Number of cigarettes squared	0.000	0.000	0.001	0.006
Constant	0.964***	0.042	4.576**	2.053
Risk error (μ)				
Constant	0.264***	0.013	0.270***	0.013
Time error (ν)				
Constant	0.919***	0.211	0.652***	0.148
N	20850		20850	
log-likelihood	-11726.62		-11428.276	

Results account for clustering at the individual level
* *p*<0.10, ** *p*<0.05, *** *p*<0.01